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Gender and STEM: Understanding Segregation in Science, Technology, Engineering and Mathematics

Edited by
Maria Charles and Sarah Thébaud

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Special Issue Editors

Maria Charles

Sarah Thébaud

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Special Issue Editors
Maria Charles
University of California—Santa Barbara
USA

Sarah Thébaud
University of California—Santa Barbara
USA

Editorial Office
MDPI
St. Alban-Anlage 66
Basel, Switzerland

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About the Special Issue Editors

Maria Charles is Professor of Sociology, Director of the Broom Center for Demography, and faculty affiliate of the Feminist Studies Department at the University of California—Santa Barbara. Her research explores gender inequalities around the world and the cultural and structural forces that sustain them in families, educational systems, and labor markets. Charles is an elected member of the Sociological Research Association and recipient of multiple research grants and awards, including the Max Weber Award for *Occupational Ghettos: The Worldwide Segregation of Women and Men* (with David Grusky, Stanford University Press), and the Distinguished Article Award from the American Sociological Association's Sex and Gender Section for "Indulging our Gendered Selves? Sex Segregation by Field of Study in 44 Countries (with Karen Bradley, *American Journal of Sociology*). Charles received a Ph.D. in Sociology from Stanford University.

Sarah Thébaud is Associate Professor of Sociology and faculty affiliate of the Broom Center for Demography and the Technology Management Program at the University of California—Santa Barbara. Her current research examines how organizational practices and stereotypic beliefs about men's and women's traits and abilities matter for understanding phenomena such as men's overrepresentation in entrepreneurship, science, and engineering, the gender division of household labor, and gender gaps in workplace authority. Thébaud's research has been supported by the National Science Foundation and the Kauffman Foundation, among others, and has appeared in academic journals such as the *American Sociological Review* , *Administrative Science Quarterly*, Gender & Society , and Social Forces . It has also been featured by several national and international media outlets. Thébaud received her Ph.D. in Sociology from Cornell University.

Preface to "Gender and STEM: Understanding Segregation in Science, Technology, Engineering and Mathematics"

This volume features thirteen original chapters on the causes and consequences of gender segregation in scientific, technical, engineering, and mathematics ("STEM") occupations and fields of study.

Although women have made great strides in equalizing access to labor markets and higher education, many STEM fields—particularly in the physical sciences and engineering—remain strongholds of gender segregation in the United States and other reputably gender-progressive societies. Policymakers, business leaders and activists have launched countless initiatives to diversify access to lucrative, high status occupations and ameliorate labor shortages that diminish innovation and competitiveness.

Contributors to this volume apply diverse theoretical lenses and methodological approaches to understand the individual, interactional, organizational, and cultural dynamics that drive this segregation in the United States. Results show that the gender composition of scientific and technical fields varies a great deal over time and across organizational contexts and socio-demographic groups defined by race, ethnicity, class, and sexuality. But despite this variability, STEM work and STEM workers in the United States are widely presumed to be naturally and inevitably masculine. Research presented here reveals how these stereotypes combine with cultural beliefs about natural and fundamental differences between men and women to produce gendered aspirations and reinforce inequalities in the US scientific and technical workforce.

The book is divided into five sections. In the introductory section, we review diverse theoretical accounts of occupational gender segregation and consider how they accord with the available evidence on gender inequality in STEM fields that is published here and elsewhere. We argue that support is strongest for cultural accounts that allow for a dynamic interplay between individual-level traits and the broader sociocultural environments in which they develop. The four subsequent sections consider the gender typing of scientific and technical fields in different life phases and in different institutional domains. Section two includes four contributions on the development of STEM aspirations and expectations. This is followed by section three which includes two articles on how STEM educational trajectories are affected by gender and race/ethnicity within American universities. Contributors to section four consider the transitions from education to STEM labor markets, and the fifth section explores inequalities by gender and sexuality within academic and nonacademic STEM workplaces.

Articles in this book were originally published as a special issue of Social Sciences that we guest-edited. We thank the *Social Science* editors for their administrative support and dozens of anonymous reviewers who offered crucial insights and suggestions on multiple drafts of the articles in this volume. We also thank Russell Thébaud for his excellent design work on our cover. We are most grateful to the contributing authors for their thought-provoking research and their ongoing efforts to illuminate the sociocultural dynamics of gender inequality in STEM and beyond.

Maria Charles, Sarah Thébaud
Special Issue Editors

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Article

Segregation, Stereotypes, and STEM

Sarah Thébaud and Maria Charles *

Department of Sociology, University of California—Santa Barbara, Santa Barbara, CA 93106-9430, USA; sthebaud@soc.ucsb.edu

* Correspondence: mcharles@soc.ucsb.edu

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Abstract: Scientific, technical, engineering, and mathematical (STEM) occupations are strongholds of gender segregation in the contemporary United States. While many Americans regard this segregation as natural and inevitable, closer examination reveals a great deal of variability in the gendering of STEM fields across time, space, and demographic groups. This article assesses how different theoretical accounts accord with the available evidence on the gender composition of scientific and technical fields. We find most support for accounts that allow for a dynamic interplay between individual-level traits and the broader sociocultural environments in which they develop. The existing evidence suggests, in particular, that Western cultural stereotypes about the nature of STEM work and STEM workers and about the intrinsic qualities of men and women can be powerful drivers of individual aptitudes, aspirations, and affinities. We offer an illustrative catalog of stereotypes that support women's STEM-avoidance and men's STEM-affinity, and we conclude with some thoughts on policy implications.

Keywords: gender; STEM; segregation; stereotypes; culture; work; occupations; science; inequality

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For more than three decades, American educators, policy makers, activists, and business leaders have engaged in research and policy initiatives to increase the presence of women and other underrepresented groups in scientific, technical, engineering, and mathematical (STEM) occupations and fields of study. These efforts have been motivated by interests in broadening opportunities in lucrative, high-status occupations and in ameliorating acute STEM labor shortages that are believed to threaten national prosperity, private profits and the public welfare.

Despite wide-ranging research and policy efforts, STEM occupations remain strongholds of gender segregation in the contemporary United States. Women made up nearly half of the US labor market in 2015, but only 28% of all scientific and technical workers. Within STEM, gender segregation is also very strong, with women comprising 48% of life scientists and 60% of social scientists, but only 28% of physical scientists and 15% of engineers (NSF 2018, Appendices 3–12).[1] While some fields have integrated over time, others have become more segregated. Women's share of US bachelor's degrees in computer science, for instance, declined from 28% to 18% between 2000 and 2015 (NSF 2018, Appendices 2–21).

While many Americans understand men's dominance of scientific and technical work as natural and universal, the gender typing of STEM fields varies a great deal across space, time, and socio-demographic groups. Recent comparative studies have shown that scientific degree recipients are disproportionately *female* in Iran, Saudi Arabia, Romania, and Georgia, for example, and that the gender gap in children's STEM aspirations is larger in more affluent societies (Charles 2011a, 2017;

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1 Even within engineering women and men tend to do different work: about 10% of mechanical and electrical engineers are women, compared to 20% of civil engineers (ibid.).

Stoet and Geary 2018; see also Women in Engineering in Predominately Muslim Countries n.d.). Within the United States, the gender composition of STEM fields has varied over time as well—including in computer programming and quantitative social science, which have transitioned from female- to male-labeled since their founding (Luker 2008; Abbate 2012; Ensmenger 2015). STEM gender gaps also vary in size across groups defined by race, class, and immigration status (Xie and Shauman 2003; Ma 2009; Nores 2010). In 2015, for instance, 22% of Black engineers, but only about 14% of White, Asian, Hispanic and Latino engineers were women in the US (Wong and Charles 2018).

This strong contextual variability suggests an important role of sociocultural factors in the gender segregation of scientific and technical work. Contributors to this volume explore these factors through in-depth analyses of the STEM-relevant experiences and outcomes of US-based workers and students.

The current article assesses how different theoretical accounts of segregation accord with available evidence on the gender composition of STEM fields. We find most support for accounts that allow for a dynamic interplay between individual-level traits and the broader sociocultural environments in which they develop. The evidence suggests, in particular, that Western cultural stereotypes about the nature of STEM work and STEM workers, and about the intrinsic qualities and relative social status of men and women, can be powerful drivers of gendered aspirations and affinities. Our discussion of the existing theoretical and empirical literature is followed by an illustrative catalog of stereotypes that have been found to support women's STEM-avoidance and men's STEM-affinity. We conclude with some thoughts on policy implications.

1. Why are STEM Fields so Segregated?

Sociologists commonly distinguish between micro- and macro-level explanations for gender inequality. The former consider characteristics of persons (e.g., individual workers and employers) and the latter focus on characteristics of larger units (e.g., organizations, national societies). Below, we consider how each framework accords with the available evidence on gender segregation of STEM fields, and how micro- and macro-level processes may interact to produce highly resilient forms of gender inequality.[2]

1.1. Micro-Level Explanations

The explanations of gender segregation that are most popularly resonant invoke the personal traits of workers and employers. These are often dubbed "supply-side" and "demand-side" accounts, respectively, in reference to the sellers and buyers of labor depicted in classical microeconomic theory.

Supply-side explanations focus on differences between men and women in aptitudes, preferences, or workplace productivity (Becker 1985; Mincer and Polachek 1974). The segregation of STEM fields might, for example, be attributed to women's stronger orientation toward interpersonal relations and care, or to men's greater investment in the requisite human capital or greater capacity for analytical thinking. Biologically-based supply-side accounts emphasize sex hormones and brain structures as drivers of gendered behaviors and divisions of labor (Baron-Cohen 2003; Ceci and Williams 2011). Socialization accounts emphasize the sorting of people into binary sex categories at birth and the rewards (sanctions) that accrue for gender-conforming (-nonconforming) behaviors. Because gendered traits are eventually internalized, adult women are expected to prefer roles that draw upon feminine traits, and adult men are expected to prefer roles that draw upon masculine traits (Parsons and Bales 1955; Marini and Brinton 1984).

Explanations emphasizing gendered workers resonate widely and align well with the ubiquitous "Mars and Venus" mythology that depicts men and women as innately "opposite" sexes (Gray 2012). High-profile supply-side accounts of gender inequality in STEM include a 2005 speech by Harvard president Lawrence Summers, and a 2017 memo by former Google engineer James Damore,

[2] For a more general review of the literature on occupational gender segregation, see Wong and Charles (2018).

both attributing women's underrepresentation to fundamental gender differences in abilities and preferences. These accounts generate fierce resistance among advocates for equality because they seem to blame women for their lesser status in these fields and suggest that the current gendering of occupations is inevitable.

Most social scientists view supply-side explanations as inadequate—among other things, because the gender typing of occupational roles varies strongly across time and space, and over the individual life course (Jacobs 1989; Tolley 2003; Penner 2008; Grier 2005; Charles 2011a, 2017) and because measurable differences between men and women are too small to account for the extreme patterns of segregation observed in many occupations and workplaces. Even when men and women differ on average on some aptitude or personality trait, between-gender differences are typically much smaller than within-gender differences, and the size of observed gender gaps frequently vary by context or disappear when men and women have the same status (Epstein 1988; Ridgeway and Smith-Lovin 1999; Eagly 1995; Hyde 2005; Stoet and Geary 2018). An exhaustive analysis of the science of sex differences accordingly concludes with the following observation:

> Personality traits and predispositions are not identical in individuals, but they are also not well captured by the binary system of gender . . . We aren't blank slates, but we also aren't pink and blue notepads (Jordan-Young 2010, p. 290).

Even gendered divisions of family labor, a central focus of neoclassical micro-economists (Mincer and Polachek 1974), appear to have little power to explain differences in career trajectories between women STEM and non-STEM professionals (Glass et al. 2013). In this volume, for instance, Sassler et al. (2017) find that differential STEM persistence of men and women degree holders in computer science and engineering are unrelated to family factors, and Shauman (2017) shows that gender disparities in early career outcomes of STEM doctorates cannot be attributed to actual parenthood/marriage patterns, as is commonly presumed. Overall, it appears that differences between men and women in the typically invoked individual-level characteristics have limited explanatory power for understanding gender-differentiated STEM career paths.

Among the standard "supply side" variables, occupational aspirations and expectations typically show the most robust effects on career trajectories: aspirations are strong predictors of occupational outcomes, and gender is a strong predictor of occupational and educational aspirations, holding constant a host of other factors, including employment continuity and expectations for marriage and children (Okamoto and England 1999; Xie and Shauman 2003). The causes of gendered occupational aspirations are less well documented. Further on, we identify one important causal factor: the cognitive biases that can result from stereotypes about hard-wired gender difference (i.e., "gender-essentialist" belief systems).

Demand-side explanations switch the focus from attributes of men and women workers, to actions and attributes of employers and clients (and, at the macro level, characteristics of firms and policy regimes). The simplest demand-side explanation for labor market inequality is that employers with "tastes for discrimination" are willing to pay a wage premium to hire members of preferred groups (Becker 1957).[3] Although economic theory holds that discrimination puts employers at a competitive disadvantage, some economists have attributed its persistence to employers' imperfect information about the relative productivity of potential workers. According to "statistical discrimination" theory, employers may seek to maximize profits by discriminating against groups whose members they believe are less productive on average (Phelps 1980). For example, if an employer believes that the average woman has a weaker capacity for analytical reasoning than the average man (and if analytical

[3] Employer discrimination also figures prominently in queuing theory, which holds that modern labor markets are built around two queues: a labor queue in which employers rank the desirability of employees, and a job queue in which workers rank the attractiveness of jobs (Reskin and Roos 1990). Because women are systematically ranked below men in the labor queue, they are overrepresented in the least attractive jobs.

reasoning were difficult to measure directly), it might seem rational to discriminate against all women in hiring for jobs that place a premium on analytical reasoning.

An important point here is that employers' personal beliefs about average gender differences need not be true to produce extreme gender segregation. Because many employers are exposed to the same taken-for granted cultural stereotypes about men's and women's average capacities, statistical discrimination can be a powerful mechanism for translating cultural beliefs about gender difference into gendered individual preferences and outcomes (Bielby and Baron 1986). We discuss this sort of macro-micro interplay further on.

Gender discrimination is difficult to measure—in part because it is illegal in the United States and few people will admit to it. Some of the most compelling evidence of discrimination in STEM hiring has been gathered through experiments and audit studies. One double-blind audit study demonstrated, for example, that STEM faculty members were less likely to hire female than male candidates for a lab manager position, because women were perceived to be less competent (Moss-Racusin et al. 2012; see also Goldin and Rouse 2000). Other research has shown that faculty are more likely to respond to email requests for graduate mentoring from persons with male, white-sounding names (Milkman et al. 2015) and that scientific papers are judged to be of higher quality when attributed to a male author (Knobloch-Westerwick et al. 2013). In this volume, Blair-Loy et al. (2017) provide new evidence of unequal treatment in the STEM hiring process in the form of videotaped job talks that show more interruptions of women than men candidates for faculty engineering positions.

Importantly, supply- and demand-side processes can reinforce one another by generating self-fulfilling prophesies. For example, knowledge (or even rumors) of discrimination in male-dominated science and engineering fields may influence occupational aspirations, leading some girls and women to forego STEM training and thereby reducing their future competitiveness in these fields. STEM avoidance by a few girls can have multiplier effects because adolescents respond strongly to standards set by same-gendered peers (Legewie and DiPrete 2014). Discriminatory treatment is also reinforced by behavioral responses to unbalanced gender ratios. In her classic ethnography, Kanter (1977) showed how the intense visibility and performance pressures experienced by numerical minorities ("tokens") in work organizations give rise to stereotype-confirming behavior and interactions that reproduce existing inequalities (1977). For example, token women may react to discriminatory treatment and gender stereotyping by enacting some organizationally sanctioned version of femininity to which they can reasonably conform. The result is often constrained opportunities and feedback loops of disadvantage and personal dissatisfaction (Turco 2010; Ridgeway 2011; Banchefsky and Park 2018; Garr-Schulz and Gardner 2018).

The interactional processes that disadvantage women in male-dominated STEM workplaces are often compounded by other forms of minority status, including nonwhite or immigrant identities, and non-hegemonic forms of gender or sexuality (Fenstermaker and West 2002; Williams et al. 2014; Alfrey and Twine 2017; Cech and Pham 2017; Ma and Liu 2017; Sassler et al. 2017). In US academic physics, for example, the cultural image of the white male scientist intensifies pressure on women of color, who frequently face skepticism about their competence and belonging (Ong 2005).

1.2. Macro-Level Explanations

Gender segregation of STEM is generated within social environments that vary widely. In the following, we consider how individual aptitudes and preferences are conditioned by broader structural and cultural forces.

A first set of macro-level accounts focus on societies or countries as the unit of analysis. One influential structural theory suggests a generically egalitarian effect of socioeconomic modernization—either because discrimination is too costly to sustain in competitive market economies (Treiman 1970; Jackson 1998; see also Cole and Cole 1973 on meritocracy in science), or because countries absorb liberal universalistic cultural values from the affluent West as they modernize and develop tighter links to global institutions and world culture (Ramirez et al. 1997; Berkovitch 1999;

Meyer 2010). Consistent with these evolutionary accounts, gender equality has increased around the world on many important dimensions—in particular with respect to formal legal rights and participation in labor markets and educational institutions. In other respects, however, inequality has proven to be highly resilient in the industrial West. Today some of the most gender-segregated STEM workforces are found in highly affluent, reputably gender-progressive societies (Charles 2011b, 2017; Stoet and Geary 2018).

The "postindustrial" restructuring of economies has had similarly uneven effects on gender stratification, supporting rising rates of female employment while also contributing to the consolidation of pink-collar "occupational ghettos" (Charles and Grusky).[4] These shifting labor market dynamics have been reinforced by the postwar expansion of higher education—in particular, the proliferation of two-year and vocational institutions and the expansion of programs such as human development, home economics, and teacher education, which were explicitly designed to appeal to what were understood to be women's natural interests (Bradley and Charles 2004). In short, women have often been incorporated *as women* into expanding labor markets and educational institutions. And since the middle of the twentieth century, "women's work" has not included most STEM occupations.

Gendered employment patterns are also heavily shaped by national policies and traditions. Social arrangements—for example, relating to hours, working conditions, family leaves, childcare, worker protection, and taxation—regulate individual behavior and reproduce normative models of work and family (Buchmann and Charles 1995; Gornick and Meyers 2003; Thébaud 2015; Ecklund and Lincoln 2016). Social democratic policy regimes, which offer greater support to working parents, tend to promote more egalitarian family structures and higher rates of women's full-time employment (Charles and Cech 2010; Pedulla and Thébaud 2015; Hegewisch and Gornick 2011), but they are at best weakly related to gender segregation in STEM—as evidenced in the highly segregated scientific and technical labor forces found in policy-progressive Scandinavian countries (Charles and Bradley 2006; Charles 2011a).

A second set of macro-level accounts focus on characteristics of workplaces and work organizations. For instance, much has been written about the role of organizational bureaucratization in reducing the operational salience of masculine, white, and heteronormative biases. Some studies show that technology firms that emphasize formal rules and procedures—as opposed to informal peer-group control—are characterized by less discrimination and more opportunities for recruitment and advancement of women scientists (McIlwee and Robinson 1992; Baron et al. 2007). Other analyses suggest that formal bureaucracy obscures discrimination in "gendered organizations" by advancing structures that presume male workers but discourses that leave the gender of the ideal worker unspecified (Acker 1990).[5] In one Swedish information and communication technology firm, for example, requirements for travel and long hours away from home were found to restrict women's ability to acquire advanced technological expertise and resulted in their concentration in administrative roles (Holth et al. 2017). But while workplace expectations for high temporal and spatial availability tend to elicit gendered responses (Blair-Loy 2003; Zippel 2017), they appear to affect advancement and retention in similar ways across different sorts of professional occupations (Glass et al. 2013). They do little, therefore, to explain the extreme gender segregation of STEM fields in particular.

Given the limited explanatory power of other accounts, it is not surprising that a growing body of research centers on the uniquely gendered cultural elements of STEM disciplines and work environments in Western societies and organizations. Gender is a dominant cultural frame that

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[4] Many expanding industries (e.g., in childcare, health, elementary teaching) produce services that are symbolically or functionally linked to women's domestic work, and high labor demand has led some employers to reorganize these jobs to appeal to married women—for example, through part-time scheduling (Oppenheimer 1973; Goldin 1990; Charles and Grusky 2004).

[5] Other organizational characteristics that have been linked to occupational gender segregation include firm size, personnel policies and practices, skill requirements, opportunities for team work, unionization rates, women's presence in management, and workplace traditions (Bielby and Baron 1986; Baron et al. 1991; Reskin and McBrier 2000; Smith-Doerr 2004).

organizes everyday social relations, shapes individual identities, and inscribes gender inequality in social and economic institutions (Ridgeway 2011). In contemporary Western societies, persons are widely presumed to occupy one of two distinct gender categories, and many work tasks are presumed to be intrinsically masculine or feminine (Bem 1993; Faulkner 2000; Nosek et al. 2002; Des Jardins 2010). Many people believe, therefore, that occupations like engineering and preschool teaching are highly segregated *because* they require aptitudes and bodies that map neatly onto the "Mars and Venus" gender dichotomy. As such, occupations themselves become implicitly categorized by gender, just as people do. In the case of STEM, this categorization is often reinforced by the distinctively masculine cultural beliefs, norms, and practices that pervade STEM educational and work environments.

Of course, an occupation's gender composition depends upon diverse factors, including the economic and social conditions operative at the time of its expansion (e.g., labor shortages, technological developments, barriers to entry) and the functional and symbolic proximity of its task profile to work historically done by men or women. But, once segregated, occupational gender labels become imprinted in the popular imagination and are absorbed at an early age. "Draw-A-Scientist" studies show, for example, that young American children have taken for granted the masculinity of STEM workers for at least five decades (Miller et al. 2018). These gender labels are naturalized as people identify aspects of the work process (e.g., physical, analytical, or emotional demands) that support cultural stories about the occupation's intrinsic masculinity, often remembering evidence that is consistent with their preexisting beliefs and discounting evidence that undermines them (Bourdieu 1975; Milkman 1987; Fiske 1998; Tolley 2003; Charles and Grusky 2004). Greater exposure to women scientists and proximity to same-gender role-models appear to weaken these stereotype effects, however (Miller et al. 2018; Jacobs et al. 2017; Misra et al. 2017).

Evidence is growing that cultural beliefs associated with STEM occupations can bias cognition and affect individual decision-making, thereby reproducing occupational segregation. We believe that this interplay between macro and micro-level processes offers a particularly fruitful explanation for the resilience of gender segregation in STEM in advanced industrial societies.

1.3. Micro-Macro Interactions: Cultural Stereotypes into Aspirations

The cultural gender stereotypes that we associate with people and jobs reproduce occupational segregation by affecting both labor demand and labor supply. On the demand side, the most obvious intermediary mechanisms are discrimination against workers and applicants whose gender does not "fit," or align with, the gender of the job, gendered recruitment practices, and biased assessments of individuals' relative qualifications (Becker 1957; Phelps 1980; Bielby and Baron 1986; Foschi 1996; Heilman 2001). On the supply side, stereotyping reinforces segregation by leading people to make gender-conforming choices that affirm their masculinity or femininity, and avoid social sanctions and discriminatory work environments (West and Zimmerman 1987; Ridgeway 2011; Cech 2013; Blair-Loy et al. 2017; Weisgram and Diekman 2017).

Research also shows that gender stereotypes affect supply-side processes by biasing people's understandings of their own aptitudes and affinities. That is, people may choose gender-conforming occupations because they believe, perhaps erroneously, that they will be more skilled at this work or enjoy it more (Correll 2004; Charles 2017). These biased self-understandings are powerful because they can shape occupational aspirations, and behaviors even in the absence of direct structural constraints, discrimination, or individual-level socialization.

For instance, recent research documents how cultural gender beliefs affect people's confidence in their abilities to carry out the technical tasks and assume the identities associated with gender-atypical occupational roles (Thébaud 2010; Cech et al. 2011; Stets et al. 2017; Hill et al. 2017; Sanabria and Penner 2017; Wynn and Correll 2017). An important experimental study by Correll showed that women's exposure to (false) information about men's generally superior performance at a specific task led them to rate their own task performance lower and to express less interest than men in careers that purportedly draw upon related skills (2004). No gender gaps in self-assessments or aspirations were found when participants were exposed to the belief that men and women were equally proficient at the task.

Besides biasing self-assessments of ability, cultural gender stereotypes can also bias individuals' beliefs about their own affinities, so that they will more often expect to enjoy work that involves gender-conforming tasks. Cech (2013) finds that college students are more likely to later choose female-dominated occupations if they describe themselves in culturally feminine terms, such as emotional, unsystematic, and people-oriented. Comparative research suggests that this gender-typing of career aspirations is especially pronounced in affluent, "postmaterialist" societies (Charles and Bradley 2009; Charles 2017). In these contexts, concerns about existential security are less salient in career choices and cultural narratives emphasize "following your passions" and "doing what you love" (Inglehart and Welzel 2005; Tokumitsu 2015). Since many persons, especially adolescents, do not know in advance what they will love doing, postmaterialist career aspirations may be built more often upon stereotypes about what people like them (often same-gendered people) love. Girls, for example, may expect to enjoy work that they think will be more communal and interactive, and following these passions will probably not lead them toward the solitary science career depicted in Western popular culture. The implication is that widespread cultural beliefs about how men and women are different and what they enjoy doing contribute to career choices that reproduce the gender order but are experienced as the expression of personal likes and dislikes.

This emotional buy-in contributes to the reproduction and legitimization of gender segregation in advanced industrial societies and helps account for the surprising cross-national differences in the gender composition of STEM occupations. Whereas ideologies of male primacy—and vertical inequalities—tend to weaken in affluent Western democracies, beliefs in categorical gender difference are easily reconciled with the liberal individualistic ideals that permeate these cultures (Charles and Grusky 2004; Cotter et al. 2011; Levanon and Grusky 2016; Knight and Brinton 2017; Chatillon et al. 2018). Under these "postmaterialist" gender regimes, horizontal forms of gender segregation, such as professional women's underrepresentation in STEM fields, retain legitimacy because they are easily understood as the outcome of free choices by equal but innately different men and women.

Culture can also affect performance in a stereotype-consistent manner. Experiments on "stereotype threat" show that people do worse on tests when they fear confirming a negative stereotype about their gender (or racial) group. In one study, a significant gender gap in test performance was observed when subjects were told that men generally do better, but not when they were told that men and women do equally well on the test (Spencer et al. 1999). Beliefs in essential gender differences in aptitudes have especially strong effects in fields such as STEM, where practitioners often attribute success to innate talent (Leslie et al. 2015). This is another way in which stereotypes can be self-fulfilling.

The preceding analysis has identified diverse ways in which cultural stereotypes contribute to the gender-typing of STEM—among other things, by influencing how men and women perceive themselves, how they are treated by others, and how societies and work environments are structured. The cognitive schemas and life experiences that result from taken-for-granted cultural beliefs about men, women, and STEM produce aspirations and outcomes that are far more gender-differentiated than any underlying distribution of individual-level traits. They therefore have far more power to explain the extreme gender segregation of STEM fields observed in the contemporary United States.

In the following section, we unpack the underlying content of cultural beliefs about the gendered nature of persons and jobs that are revealed in this volume and elsewhere. By assembling these stereotypes in one place, we hope to demonstrate their prevalence, range, and potential to shape individual cognition, aspirations, and behaviors. We also aim to articulate why the culture of many STEM disciplines and occupations remain bastions of masculinity in the contemporary United States.

2. Stereotypes about Men, Women, and STEM Workers, Work, and Workplaces

Before discussing stereotypes that are specifically relevant to the segregation of STEM fields, we provide some general background on the descriptive and prescriptive content of gender stereotypes.

2.1. Descriptive and Prescriptive Gender Stereotypes

For decades, social psychologists have documented the content of cultural stereotypes about men and women (see Rudman and Glick 2008 for a summary). In the US context, men are believed to be more agentic and competent than women, whereas women are believed to be more communal than men. That is, men are not only privileged on competence-related traits like intelligence, skill, and capability, but they are also believed to be more able to get things done by being more assertive, goal-oriented, ambitious, independent, competitive, and self-interested. By contrast, women are presumed to be primarily oriented toward others—by being more warm, kind, nurturing, friendly, and polite.

One might imagine that these descriptive stereotypes would be outdated, given women's progress toward equality in the workforce and in education over the last half-century. And indeed, a recent study suggests that that the belief that women are in general less intelligent or skilled than men has waned in more recent cohorts (Eagly 2018). At the same time, though, research shows that especially high levels of intelligence or ability—characteristics like "brilliance," or "genius"—remain masculine-coded (Furnham et al. 2006; Stephens-Davidowitz 2014), and stereotypes still privilege men's ability in male-typed tasks like mathematics (Ridgeway 2011). Furthermore, there has not been any discernible change in the belief that women are less agentic than men, and stereotypes about women's greater communality are even more strongly held today than they were in earlier cohorts (Eagly 2018).

Importantly, these commonly held beliefs do not merely describe men and women (i.e., they presumably are this way), but they also set prescriptive expectations for behavior (i.e., men and women ought to be this way) (Prentice and Carranza 2002). For instance, being assertive and ambitious is intensely prescribed for men (i.e., cultural beliefs dictate that men really ought to possess this trait in order to be liked and respected by others), whereas being warm and kind is intensely prescribed for women (i.e., cultural beliefs dictate that women really ought to possess this trait in order to be liked and respected by others). This prescriptive dimension of gender stereotypes is critical for understanding persistent inequality, since it sets the foundation for several micro-interactional processes that ultimately motivate both men and women to behave in stereotype-consistent ways (Heilman 2001; Rudman and Glick 2008). It is noteworthy, however, that normative pressures to conform tend to be particularly strong for men because society places greater value on the traits and abilities associated with men and masculinity than on those associated with women and femininity (see e.g., Ridgeway 2011). For instance, Rudman et al. (2012) demonstrate that the traits that men are supposed to possess are high in status (e.g., competitive), whereas the traits that women are supposed to possess are more neutral in status (e.g., friendly). In contrast, the traits that men are not supposed to possess are low in status (e.g., emotional) and the traits that women are not supposed to possess are high in status (e.g., aggressive). As such, it is not surprising that normative expectations and perceptions—especially when enforced by same-gender peers—are particularly relevant for understanding men's behavior, given that gender conformity translates into a status advantage for men but not for women (Kimmel 2008; Pascoe 2007).

2.2. Stereotype Content and Inequality in STEM

Both the descriptive and prescriptive content of stereotypes about men and women have direct implications for inequality in STEM. To begin, contemporary stereotypes about STEM workers, work, and workplaces simultaneously privilege masculine-coded traits like high levels of intelligence and agency while devaluing the communal traits that women supposedly possess. Many STEM fields, especially the more male-dominated ones like physics and computer science, share a culture in which high levels of raw talent and brilliance are viewed as essential to success. Recent studies suggest that differences across fields in the strength of this "brilliance narrative"—both among academics and within the broader culture—map directly onto the distribution of men and women across fields (Meyer et al. 2015; Leslie et al. 2015).

Beyond prizing high levels of raw intelligence, many science and engineering disciplines idealize workers who embody such stereotypically masculine traits as assertiveness, competitiveness, dominance, and strong identification with work (Bailyn 2003; Cooper 2000; Williams et al. 2006). Furthermore, a "geek" stereotype is today associated with many STEM fields and workers (Cheryan et al. 2009; Varma 2007; Ensmenger 2015). The "geek" cultural image is of a person who is exclusively interested in and focused on scientific or technological endeavors (e.g., someone who stays up all night coding). When the "geek" image is not valued, other forms of masculinity and masculine identity may be present. For instance, some technology workplaces have been found to valorize "brogrammers"—who are supposedly more sociable and outgoing than "geeks," but only in the way that a stereotypically party-focused fraternity brother would be (Alfrey and Twine 2017; Wynn and Correll 2014). Both the "geek" and frat-like "brogrammer" cultural images exemplify the agentic qualities that women supposedly lack, and they devalue the communal traits that women supposedly possess: such individuals are thought to lack "social skills," to be disconnected emotionally, and/or to be less caring toward others.

In our view, the broader implication of these numerous linkages between masculine traits and abilities and many STEM disciplines, workers, and workplaces is that men are not only perceived as a better "fit" for these social spaces from a descriptive point of view, but they are also likely to experience greater social pressure and rewards for pursuing them. That is, by pursuing one of these fields, a man can align his presumed abilities and interests with a high-status career, while also living up to prescriptive expectations for how he ought to behave. As such, his occupational choice is likely to increase his chances of being liked and respected as a man. The calculation is less clear for a woman. While she may be respected for pursuing a high status career, her choice may not necessarily be perceived as a good fit for her interests or abilities, and it may not win her greater admiration or respect as a woman. Instead, she may risk discrimination, dislike, or ostracism for being "too" aggressive, ambitious, etc. (see e.g., Heilman 2001 on backlash effects). As such, men are more likely to experience strong incentives to pursue STEM fields and to retain commitment to them, whereas this not always the case for women, notwithstanding the material advantages of STEM careers.

This argument is supported by recent research on the linkage between masculine traits and abilities, STEM, and men's and women's decision-making. Gendered beliefs about the relationship between high levels of innate intelligence and qualification for particular pursuits have been shown to affect career aspirations from an early age. One recent study found that, by age six, girls are less likely than boys to believe that members of their gender are "really, really smart," and that they begin to avoid activities believed to be for children who are "really, really smart" (Bian et al. 2017). In this volume, Hill et al. (2017) similarly find that middle schoolers who believe that raw intelligence is a fixed trait from birth are more likely to endorse the idea that boys are better than girls at science and less likely to believe that they themselves could be a scientist. Sanabria and Penner (2017) also show that boys are more likely than girls to persist in STEM majors after failing an introductory calculus, perhaps because stereotypes about gender differences in mathematics ability make boys less likely to attribute poor test performance to a lack of intrinsic ability.

Presumptions of greater male scientific and technical competence also reinforce gender segregation through their effects on workplace interactions. Experimental studies show, for example, that women's expectations of discrimination and gender bias reduces their anticipated sense of belonging and their interest in STEM careers (Moss-Racusin et al. 2018). Cech and Pham (2017) deepen our knowledge about this relative devaluation of feminine traits in STEM workplaces by illustrating the ways that lesbian, gay, bisexual and transgender (LGBT) workers—whose gender performance often deviates from normative expectations—experience disadvantage in STEM workplaces. It is this very disconnect between the cultural traits linked to women and the cultural traits linked to normative STEM workers and STEM workplaces that catalyzes inequality.

Men's stronger interest in and greater likelihood of persistence in STEM fields is also driven by gender-differentiated self-perceptions of fit and ability (Cheryan et al. 2009; Wynn and Correll 2017) and the application of double standards for competence (Blair-Loy et al.; Foschi 1996). Both of these mechanisms arise from the mismatch between expectations for STEM workers and expectations for women's behavior. Such stereotyping processes are especially insidious because they matter even when an individual personally disagrees with them (Ridgeway and Correll 2004). That is, merely knowing that most other people hold certain beliefs about gender and STEM is enough to bias attitudes and behaviors. This is one reason why the content of stereotypes often remains relatively stable even in the face of changing occupational preferences and choices.

Finally, it is not just stereotypes about STEM workers and STEM workplace cultures that create a gender mismatch. As much of the research in this volume shows, stereotypes about the content of STEM work itself can deter women. For instance, many young people endorse the stereotype that science careers are not compatible with having a family. Weisgram and Diekman (2017) show that this belief, whether true or not, powerfully reduces many young women's interest in pursuing a science career. Similarly, Kyte and Riegle-Crumb (2017) find that holding the cultural belief that science is socially relevant—e.g., that science can help people or solve everyday problems—positively predicts young women's, but not young men's, intentions to major in a STEM field.

Sociocultural processes like these offer a fruitful alternative to the standard individual human-capital and family-status explanations for gender differences in STEM entry and persistence. The stereotypes identified here and elsewhere in the volume are important not only because they encourage social stigma and discriminatory treatment by others, but also because they cause people to under- or over-estimate their own qualifications and their own potential affinity for gender-nonconforming work. As a result, men and women (boys and girls) are likely to aspire to different occupations, pursue different educational and occupational pathways, and experience their work interactions and environments in gendered ways. In liberal egalitarian societies, many forms of gender inequality are reproduced and legitimated through the conversion of cultural stereotypes into gender-conforming preferences—and then into seemingly free choices by different-but-equal men and women (Charles 2011b).

We turn next to consider the practical implications of this research: What, if anything, might be done to diversify STEM occupations?

3. Policy Implications

Experimental and audit studies provide strong evidence that women's underrepresentation in scientific and technical fields is at least partly attributable to cultural gender stereotypes and discrimination, which can be converted subsequently into gender-specific aspirations and choices. Even if the composition of STEM occupations reflects gender-differentiated career aspirations, this segregation may be problematic for at least three reasons. First, history shows that "separate but equal" principles generally produce unequal outcomes. This is evident, among other things, in the lower pay in women's than men's occupations (Levanon et al. 2009). Second, gender segregation has cultural feedback effects, reinforcing stereotypes and limiting perceived educational, family, and career options of subsequent generations. And third, women (and racial/ethnic minorities) represent an untapped labor pool globally in fields such as engineering and computer science, where shortages threaten to undermine national development or competitiveness. These concerns have motivated myriad initiatives by governments, non-governmental organizations, and industry leaders around the world to broaden and diversify opportunities in scientific and technical occupations and fields of study.

The research presented in this volume suggests that gender integration will not come easy and will partly depend on increasing girls' and women's interest in STEM. This will in turn depend upon the erosion of two kinds of cultural stereotypes: those that depict women as intrinsically ill-suited for STEM work, and those that depict STEM work as uncreative, solitary, and masculine. While cultural change of this sort can only occur gradually, some efforts toward counter-stereotype programing are evident in the growing popularity of toys like GoldieBlox engineering kits and women Lego scientists, which provide parents of young girls with alternatives to toy store pink-aisle marketing. Also challenging male math nerd stereotypes are efforts to rebrand STEM as compatible with conventional femininity. These include books like *Kiss my Math* and *Hot X: Algebra Exposed* by actress Danica McKellar, and even an updated Barbie doll in 2010. While her 1992 Teen Talk sister recited canned phrases like "Math class is tough," and "Let's go shopping," Computer Engineer Barbie presents computing as both feminine and fun—a "geek chic" that essentially replaces one set of stereotypes with another.

A more aggressive strategy for reducing the salience of gender stereotypes would be to create more opportunities for girls and boys to learn directly about gender-nonconforming fields and about their own abilities to enjoy and excel in them. Expanded high school graduation requirements, including in mathematics, computer science, and engineering could help reduce reliance on stereotypes and increase girls' confidence in their mathematical and technical ability. Although such policies would seem to be at odds with American ideals of individual choice and self-expression, research suggests that they might also weaken penetration of gender stereotypes and reduce peer pressure in course taking. Comparative studies show that the gender gap in STEM aspirations and outcomes tends to be smaller in countries and schools where curricular choice is reduced or delayed and where high school science and mathematics curricula are stronger (Federman 2007; Charles and Bradley 2009; Cheryan et al. 2009; Legewie and DiPrete 2014; Scheeren et al. 2018). This may be because reluctance to transgress gender norms declines with age (Gerson 1985; Jacobs 1989), or because exposing students to a broader array of fields provides them with better information about what they like and what they are good at.

In India, for example, a strong national mathematics curriculum makes girls more confident in their ability to learn computer skills, even if they are less likely to have computers at home, than their American counterparts (Varma and Kapur 2015). In Malaysia and India, where women earn about 45% of information and communication technology (ICT) degrees, computing is viewed as a woman-friendly profession that offers a safe and pleasant indoor working environment. This presents a sharp contrast with the male hacker image in the United States, where women earn only 23 percent of ICT degrees (Margolis and Fisher 2002; Lagesen 2008; Varma and Kapur 2015; UNESCO 2018).

But mandated early exposure will backfire without careful attention to the culture and organization of STEM classrooms and workspaces. Encouraging a sense of belonging for underrepresented groups requires work, study, and family environments that include diverse role models, supportive peer networks (including summer and afterschool clubs like Women in Engineering), and freedom from gender stereotypes and discrimination. Even the physical environment can matter. One experiment by Cheryan et al. (2009) showed that exposure to stereotype-consistent computer science classrooms (e.g., with Star Trek posters and video games visible) decreased girls', but not boys', interest in a computer science major, and that gender differences in interest were smaller when subjects were exposed to classrooms that did not conform to current stereotypes (e.g., with nature posters and phone books visible). College website descriptions may also attract more women by including information on the social relevance and collaborative nature of engineering (Da Costa and Stromquist 2018).

Some elite universities have recently implemented organizational changes aimed at undermining stereotypes about computer science work and diversifying the "boy hacker" culture. Changes have included revamping introductory computer science courses to offer a more inclusive and socially relevant curriculum, and increasing mentorship and peer support of underrepresented groups. Increases in women's share of computer science graduates have been impressive, going from 10% to 40% in five years at Harvey Mudd College, for example (Cheryan et al. 2009).

Once women have entered a STEM job, organizations and governments will need to develop policies and practices that keep them there. Policies relating to work hours, flexible scheduling, family and sick leave, and childcare are important, but research shows that it is not enough to *have* these policies. Workplaces must have cultures that support their *use*—by both women and men. True or not, many STEM workers report stigma associated with using family accommodation policies (Cech and Blair-Loy 2014).

A key finding from the historical, experimental, and interview-based research reported in this volume and elsewhere, is that individual occupational preferences are social products. Aspirations for STEM work are shaped by the (real or perceived) culture of STEM fields and by deeply rooted beliefs about the intrinsic natures of men and women. American girls who aim to "study what they love" might be just as passionate about computer science and engineering as they are about teaching and nursing if they had more chances to find out whether they love these STEM fields (e.g., through required courses, after school clubs, or summer programs for underrepresented groups), and their passion might grow if they could more easily imagine themselves fitting into these professional cultures. Counter-stereotype programming, and more exposure to women scientists might help them make that leap of imagination.

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Article

Perceptions of the Social Relevance of Science: Exploring the Implications for Gendered Patterns in Expectations of Majoring in STEM Fields

Sarah Blanchard Kyte [1,*] and Catherine Riegle-Crumb [2]

1 Education & Employment Research Center, Rutgers University, 94 Rockafeller Road, Second Floor, Piscataway, NJ 00854-8054, USA
2 Population Research Center, The University of Texas at Austin, 305 E. 23rd Street, Stop G1800, Austin, TX 78712-1699, USA; riegle@austin.utexas.edu
* Correspondence: sfblanchard@utexas.edu; Tel.: +1-512-475-8640

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Abstract: Despite efforts to increase participation in science, technology, engineering and math fields (STEM), the role of students' perceptions of the social relevance of science in guiding their expectations to major in STEM remains largely unexplored. Though science education scholars predict that perceptions of social relevance likely matter equally for boys and girls, gender scholars suggest that these perceptions should matter more for girls than boys. Using longitudinal data from a large, urban, low-income, and predominantly minority-serving district, this study examines the potentially gendered role of perceptions of social relevance in ninth graders' expectations to major in STEM. Further, it examines these dynamics with respect to expectations to major in any STEM field as well as expectations to major in specific STEM fields. Findings largely support the perspective of gender scholars; perceptions of the social relevance of science positively and significantly predict female, but not male, students' intentions to major in STEM (vs. non-STEM fields). Subsequent analyses that look at intentions to major in specific STEM fields reveal a similar pattern, such that perceptions of relevance positively predict female students' intentions to major in the biological sciences, the physical sciences, and engineering, while male students' intentions are not similarly impacted. By contrast, positive perceptions of the relevance of science predict a modest increase in interest in computer science for both boys and girls.

Keywords: social relevance; science attitudes; perceptions; gender; STEM; expectations; majors; field of study; middle school; high school

1. Introduction

Labor market analysts have been sounding the alarm regarding the need for more workers trained in science, technology, engineering and math fields (STEM) for more than a decade, as the U.S. economy is increasingly reliant on innovation and growth in these fields [1–3]. Researchers in several disciplines have attempted to understand why, despite the high demand and the accompanying high status and income associated with careers in many STEM fields, the percent of students choosing to study these fields in college has remained stagnant, or even decreased in some cases [4]. Additionally, as women remain greatly underrepresented in many STEM fields, there is a large public as well as academic discourse regarding the obstacles to recruiting and retaining female students [5,6]. Of course, the roots of the problem extend far back beyond the labor force and the postsecondary realm, as research indicates that young people make decisions quite early about whether they intend to pursue STEM fields in the future [7,8]. Though the notion of a STEM pipeline has been rightly critiqued for being too simplistic, it is nevertheless clear that adolescents' early decisions in this regard are highly predictive of their subsequent behaviors. So what factors motivate young people to choose to study STEM fields, and why are female students much less likely to make such choices?

In an effort to understand these dynamics, researchers within the fields of sociology, psychology, and education have concentrated on the role that several different factors, including academic performance, attitudes, and self-perceptions of competence play in both shaping students' decisions to pursue STEM fields and in creating and sustaining gender inequality [5,8–11]. In general, while recognizing the presence of gender socialization and stereotypes, much of the research in this area can be characterized as arguing that female underrepresentation is driven by the fact that females trail behind their male peers on the academic (e.g., high test scores) or psychological (e.g., self-confidence) factors that best predict entry into STEM fields [6,12]. Such studies have certainly helped to establish a strong foundation of knowledge regarding the factors that do (and alternatively do not) contribute to inequality. Yet, we argue that what is currently lacking are empirical studies that go beyond focusing on individuals' skills and perceptions of their own abilities and attitudes, and instead focus explicit attention on how young people actually see and make sense of science itself, and how this may have implications for gendered choices. Specifically, while research on gender disparities often assumes (either implicitly or explicitly) that girls' and boys' views of science likely play a role in shaping their decisions to later enter such fields [4,13–15], they typically do not attempt to actually measure such views nor investigate their potential impact on the choices that students subsequently make.

To address this shortcoming in the literature, in this study we examine whether and how perceptions of the social relevance of science contribute to male and female students' expectations of majoring in STEM fields. In doing so we build on insights from gender scholars [9,16,17] as well as those in science education [18–20], as each provides different predictions regarding the role of gender. Specifically, gender theories would predict that, consistent with dominant cultural beliefs about women's presumed innate preferences, perceptions of science as a domain that has broad applicability for improving human life would be much more important for influencing female students' decisions to enter STEM fields compared to male students. Yet, research in science education would instead suggest that perceptions of social relevance would be important for the subsequent decisions of both male and female students, as views of science as having meaning and utility for life outside the classroom are thought to be important motivators for all students to want to continue to study and pursue STEM fields. Thus, we will investigate whether both male and female students' future expectations are similarly positively impacted when they view scientific fields as contributing to the improvement of society, or whether instead, such views are more important in shaping the expectations of female students.

Moreover, our investigation will move beyond considering students' expectations to pursue STEM fields in the aggregate. Importantly, women's representation varies quite substantially across fields within STEM, such that a singular focus only on the broad category of STEM can obscure critical differences. Specifically, in 2013, women—who earned 57% of all bachelor's degrees—earned 59% of degrees in the biological sciences and 39% of those in the physical sciences, but only 19% and 18% of degrees in computer science and engineering, respectively [21]. Our study will examine students' expectations to major in each of these different STEM fields, and thus reveal whether perceptions of social relevance may be more important in shaping young people's future plans to pursue certain fields than others [22].

To investigate these issues, we draw on longitudinal data collected in a large, urban, predominantly minority, and low-income school district. As such, the students at the center of our study are set within an educational context that mirrors those inhabited by ever increasing percentages of young people [23]. Additionally, while minority and low-income youth are often underrepresented in STEM fields in college (and beyond), research has documented relatively high STEM interest among such student populations [24,25]. And by moving our attention past the typical focus on predominantly white populations, we gain insight into the expectations of young people who represent the changing demographics of the country.

2. Theoretical Framework

2.1. Considering the Role of Social Relevance in Shaping Females' Interest in STEM

Sociologists studying gender inequality generally posit that gender is socially constructed, such that is created and maintained through interactions at the individual level as well as the institutionalization of gendered roles and expectations at the societal level [17]. Cultural stereotypes about gender play a large role in this construction, shaping the expectations and perceptions people have for themselves and for others according to their gender [17,22]. Scholars studying gender inequality within STEM fields in particular tend to concentrate on measuring the existence and impact of stereotypes that are directly STEM-related, such as the view that males are innately better at math than females [22,26]. For example, research by Correll [9] discusses how gender-STEM stereotypes lead girls to doubt their confidence in their own ability (despite high levels of performance), subsequently leading them to be less likely than their male peers to declare STEM majors in college.

In this paper, we argue that while we have learned much from this body of research, we need to focus more explicit attention towards broad gender schemas and stereotypes that may also have implications for gendered patterns in STEM fields. Specifically, Charles and Bradley [27] argue that in contemporary Western societies such as the United States, egalitarian beliefs that all individuals should have equal opportunities in the public sphere, including access to education, exist alongside persistent cultural beliefs that men and women are essentially and fundamentally different [16,28]. Such beliefs are manifest in decisions such as the selection of a college major, where choices reflect societal beliefs about the types of work and activities for which men and women are each presumed to be differentially and innately suited to perform. For example, women are stereotyped as naturally more nurturing and concerned with the well-being of others, while men are presumed to be more individualistic, analytical, and competitive [16].

Importantly, these dominant views about essential differences between the genders also map onto perceptions of different occupational and educational fields. Some gender scholars argue that to the extent that science is not perceived to have direct applicability to helping others and benefiting society as a whole, then a decision to enter such fields would conflict with females' presumed natural preferences [8,29]. Yet in fact, there is little empirical research that focuses specifically on individuals' perceptions of science fields, and whether and how they are linked to gendered decisions about whether or not to pursue STEM. While some studies have identified gender differences in preferences for work activities, such as working alone or in teams, and linked this to subsequent gender differences in the likelihood of choosing a STEM field [5,29,30], the extant literature generally stops short of considering individuals' actual perceptions of science as a domain.

Thus in this paper, building on the insights of gender scholars, we seek to empirically investigate the claim that to the extent that science is viewed as not socially relevant—meaning it is narrow in its application and does not address societal problems—females will be much less likely than their male peers to express an intention to pursue related fields. At the same time, this perspective implies that when students do perceive science as socially relevant, this should hold more sway in increasing females' interest in pursuing STEM compared to males.

2.2. The Role of Social Relevance in Increasing STEM Interest for All Students

Of course those studying gender inequality are not the only scholars whose research focuses on increasing students' interest in STEM. Researchers in the field of science education have long focused on understanding the factors that lead to student engagement and learning in science and related fields. Classical theorists like Piaget as well as Dewey [18], called early attention to the importance of science classrooms that made explicit connections between the curriculum and the real world, recognizing the need for instruction that emphasized the broad application and power of science to transform human life. In more recent years, educational researchers have again called attention to this issue, arguing that 'school science' too often treats science fields as varied collections of abstract historical discoveries and intangible phenomenon, asking students to memorize decontextualized facts and concepts that result in their becoming bored and disinterested [31,32]. Current educational reforms are working to change this [20] and although limited in scope, there is empirical evidence that students who view science as socially relevant are more likely to remain engaged with the content and express interest in continuing to study science [19,31,33–35], and that curriculum that directly emphasizes the broad applications and benefits of science for human life can indeed be effective in promoting all students' positive views [36].

Thus educational theories as well as empirical research emphasize the power of perceptions of the relevance of science in shaping educational outcomes for all students, regardless of gender. This is not to say that the science education literature is not concerned with gender differences, yet the emphasis is typically on identifying those instances where girls trail behind boys, such as science self-confidence, and then focusing on how these could be improved [37]. And studies that explore gender differences in students' perceptions of the social relevance of science typically find that girls' and boys' views are actually very similar [32,33,38]. As such, research in this area does not typically consider these perceptions to be a likely contributor to gender differences in science interest or related future expectations.

2.3. This Study

Stepping back, the insights of two different areas of research offer two essentially competing hypotheses about the impact of perceptions of the social relevance of science on students' subsequent interest in pursuing future educational opportunities in related fields. Within science education, researchers are very concerned with students' views of science, yet generally work from the presumption that perceptions of social relevance will equally benefit all students regardless of gender. From this perspective, when both girls and boys view science as applying directly to real life and having the capacity to improve society in a myriad of ways, they will subsequently be more motivated and likely to want to continue to study it. Yet on the other hand, operating from a different theoretical lens, gender scholars call attention to dominant cultural beliefs about essential differences between males and females, which include stereotypes of women as inherently concerned with the well-being of others and the general health of society (and the planet). Thus consistent with normative gender scripts, views of science fields as being socially relevant (or not) should be more powerful in shaping the subsequent decisions of female students compared to male students. In this paper, we will empirically examine these two alternative predictions. Moreover, while women are well-represented in the biological sciences, and to a lesser extent, the physical sciences (with high representation in chemistry, a large field, but not in physics, a comparatively smaller field), they remain vastly under-represented in computer science and engineering fields at the postsecondary level as well as in the labor force [5,21]. Indeed some have argued that the reason behind these gendered patterns of representation is that women perceive computer science and engineering as abstract and disconnected from social concerns, and thus not directly related to helping others [29]. Thus we will examine whether students' perceptions of social relevance are more or less closely linked to expectations to pursue some STEM majors more than others.

3. Data and Methods

Data for this study come from the Broadening Science in School Study (BSSS) set within a large, diverse school district in one of the biggest cities in the Southwest. The vast majority of students in the district qualify for free or reduced price lunch (80%) and the student body is primarily Hispanic (62%) with smaller percentages of Black (25%) and white (8%) students. In many ways, the characteristics of this district are quite common for U.S. school children. For example, a recent study from the Southern

Education Foundation notes that 51% of students nationwide are in poverty [39]. Furthermore, within urban settings, 64% of students are eligible for free or reduced price lunch programs suggesting that such disadvantages are the norm rather than the exception [40]. Moreover, school desegregation has stalled (or perhaps even reversed) in recent years, while the share of the school-age population comprised by minority students has dramatically increased [41]. Thus a large share of students in the U.S. currently attend racially and economically segregated schools like those within our focal district.

As part of the BSSS, members of the research team collected survey data from students within this district for several years as part of a larger study aimed at understanding students' science experiences in school. Administrative data were also collected in the form of students' academic transcripts (including their grades, test scores, etc.). Finally, students' demographic data were obtained from the district including their gender, race/ethnicity, and other characteristics such as their eligibility for free or reduced price lunch.

The analytic sample for this study is comprised of a cohort of students who were 8th graders in the Fall of the 2012 academic year, and who then transitioned to high school as 9th graders the following Fall (2013). We limited the sample to those students who reported at least some likelihood that they would attend college (retaining all but 3% of students). Additionally, due to the very small percentages of students who were Asian or identified as 'other' race, we chose to restrict our analyses to white, Black, and Hispanic students.[1] Students who did not complete questions about their expected college major (our dependent variable) were excluded from the sample. Missing data on the independent variables was quite limited (ranging between 0%–6%) and was singly imputed using STATA's *impute* command. Our final analytic sample includes 935 students attending 13 high schools.

3.1. Expectations to Major in STEM

Our dependent variables are constructed from students' responses to a survey question they answered in the Fall of their 9th grade year that asked, "If you attend college, how likely is it that you would choose to major (or specialize) in each of the following fields?" This question asked students about four STEM-related fields (biological sciences, physical sciences, computer science and technology, and engineering). Student responses were reported on a scale ranging from 1 (not at all likely) to 5 (very likely). As a value of 3 represents a neutral response, we consider students who responded with a 4 or 5 for any of these four fields to be expecting to major in STEM. Our first dependent variable considers STEM expectations in the aggregate and distinguishes between those who expect to major in any of these four STEM fields vs. those who do not. In a second set of analyses we consider each field separately (e.g., distinguishing those who expect to major in the biological sciences from those that do not, those that expect to major in the physical sciences from those that do not, and so on).[2] A correlation table including all of the dependent variables and the independent variables described below are included in Appendix A (Table A1).

As seen in Figure 1, gender differences in expectations to major in STEM are quite striking. The leftmost two bars show that 47% percent of girls report an expectation of majoring in any STEM field compared to 69% of boys. Further, in examining students' plans to major in specific STEM fields, the right side of Figure 1 shows that field-specific gender gaps in STEM expectations are observable at this age. In particular, boys and girls have similar expectations of majoring in both the biological and physical sciences. Specifically, 16% of boys and 19% of girls in our sample planned to major in the biological sciences whereas 17% of boys and 18% of girls planned to major in the physical sciences

[1] Findings from a sensitivity analysis with these students retained in the sample were consistent with those presented here.

[2] Note that the dependent variables measuring students' field-specific interests are not mutually exclusive, as students indicated their expectation of majoring in each of the four fields. Among those planning to major in any STEM field, students were roughly split between those expecting to major in only one field (49%) and those expecting more than one (51%). Expectations to major in the biological and physical sciences are modestly correlated (R = 0.46), as are computer science and engineering (R = 0.34).

(neither difference is statistically significant). Furthermore, consistent with national patterns at the postsecondary level, there are very large and statistically significant gender differences in expectations to major in both computer science and engineering among the adolescents in our sample. Specifically, 35% of boys but only 21% of girls expected to major in computer science, while 53% of boys and only 22% of girls expected to major in engineering.

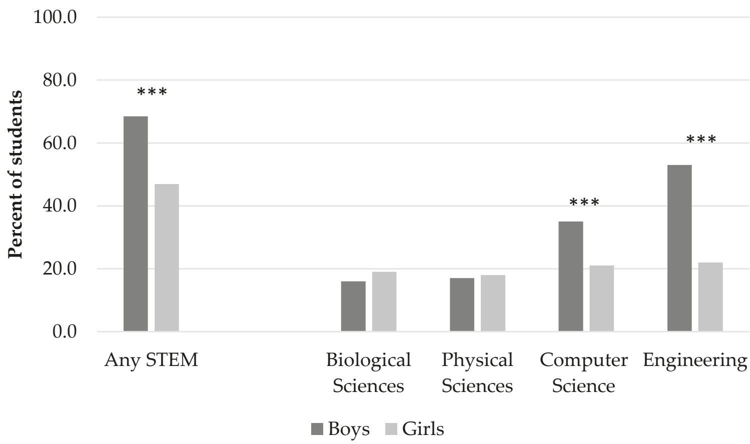

Figure 1. Expectations to major in STEM fields by gender among 9th grade students. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ~ $p < 0.10$, two tailed test.

3.2. Perceptions of the Social Relevance of Science

The independent variable at the center of this study is students' perceptions of the social relevance of science. We utilize a scale comprised of students' averaged responses in the Spring of their 8th grade year to the following items: "science helps people," "a lot of people never use science in their lives," "science is useful for solving everyday problems," "everyone uses science sometimes," "I only use science at school," and "there are all kinds of jobs or careers that use science." Items were re-coded so that a high score indicated a positive response. Because students' views of science were largely positive, we dichotomized each item to account for the skewed distribution of students' attitudes and to distinguish between those who strongly agreed vs. not (agree, disagree, strongly disagree). The Cronbach's alpha for the scale is 0.71, and an exploratory factor analysis confirms that this scale is unidimensional with similar loadings across the component items. As reported in Table 1, boys and girls had similar perceptions of the social relevance of science (pooled mean = 0.36). This is consistent with other studies that have examined young people's views of the relevance of science [32–35,38] and underscores the fact that the focus of our study is not about whether girls have a deficit in a STEM-specific resource (as evidenced by a lower mean, for example), but rather whether or not girls' expectations to pursue STEM are more strongly shaped by their perceptions of the social relevance of science.

3.3. Control Variables

3.3.1. Social Background

The multivariate models in this analysis use a set of controls for students' social background characteristics. These include students' race/ethnicity (available from administrative data), immigrant status, and a proxy for social class. Immigrant status measures whether students reported in the survey that they were born in a country other than the U.S. (coded 1) or born in the U.S. (coded 0). For social class background, we utilize a proxy that measures the number of books in one's home (commonly used in international and national studies of this age group including TIMSS). It is a dichotomous variable distinguishing between those who report having enough books in the home to fill one or more bookcases (coded 1) and those who report that their homes have fewer than enough books for one bookcase (coded 0).

Table 1 shows the descriptive statistics for these background variables, both overall and by gender. Consistent with the demographics of the school district, 73% percent of the sample is Hispanic, 10% is white, 17% is Black, and 15% were born outside of the United States. On average, students report having fewer books at home than it would take to fill a bookcase.

Table 1. Descriptive statistics for pooled sample and reported separately by gender.

	Overall		**Boys**		**Girls**		**Sig Dif**
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	
Dependent Variables							
Expects to major in STEM	0.56		0.69		0.47		***
Expected STEM major							
Biological sciences	0.18		0.16		0.19		
Physical sciences	0.18		0.17		0.18		
Computer science	0.27		0.35		0.21		***
Engineering	0.36		0.53		0.22		***
Focal Independent Variable							
Perception of the social relevance of science	0.36	0.31	0.35	0.32	0.37	0.31	
Control Variables							
Social background							
Race/ethnicity							
White	0.10		0.08		0.10		
Black	0.17		0.18		0.17		
Hispanic	0.73		0.74		0.72		
Born outside of the U.S.	0.15		0.17		0.14		
Books in the home	0.40		0.37		0.42		
Science achievement	0.03	0.77	0.04	0.77	0.02	0.76	
Science affect	0.32	0.39	0.36	0.41	0.29	0.38	*
N	935		407		528		

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ~ $p < 0.10$, two tailed test.

3.3.2. Science Achievement

Because prior research finds that students' academic achievement in STEM fields positively predicts their subsequent intentions to pursue such fields in college [6], our models include a summary measure that captures students' 8th grade science test score, as well as their science grades and level of course-taking. Specifically, students' transcripts included their score on the state accountability exam in science, as well as their cumulative grade average in science (originally scaled as 0–100). Transcripts also indicated whether or not the student was in an honors or advanced science course.[3] To avoid issues of multicollinearity and account for the different scales of each original measure, we created standardized versions of each measure, and then calculated the mean to create a summary measure used in the multivariate models that follow. Consistent with the prior literature in this area [42], girls and boys at this age are not statistically different from one another in their science achievement.

[3] As 8th graders, students in the district took a survey or overview course covering topics in earth science, biology, and chemistry.

3.3.3. Science Affect

As mentioned previously, there is a large extant research literature examining the influence of gender differences in social-psychological variables on subsequent gaps in STEM fields [9,43]. Therefore, to better assess the potentially unique contribution of our focal variable, perceptions of the social relevance of science fields, our models also take into account students' own personal feelings towards science. We include a science affect scale, comprised of students' responses to three items on the 8th grade survey: "I like science," "science is fun," and "I enjoy learning science" (Cronbach's alpha = 0.79). As before, we account for the positive skew by dichotomizing each item to distinguish between those who strongly agree vs. those who do not, before taking the mean across all items. We note here that this measure is only moderately correlated with perceptions of social relevance (R = 0.40). Moreover, boys report significantly more positive affect towards science (0.36) than do girls (0.29).[4]

3.4. Analytic Plan

The analysis in this study proceeds in two main parts. First, we examine the extent to which students' perceptions of the social relevance of science predict their subsequent expectations to major in STEM by conducting logistic regression models predicting students' likelihood of expecting to major in any STEM field (versus not). The baseline model includes students' background characteristics, academic achievement in science, and their science affect. The second model adds the measure of students' perceptions of the social relevance of science to examine whether boys and girls who perceive science as more socially relevant are in turn more likely to expect to major in any STEM field. Finally, to examine whether social relevance may matter more for girls' expectations, we include an interaction between gender and social relevance in the third model.

In the second part of our analysis, we use the same approach to predict students' expectations of majoring in each of four STEM fields—namely the biological sciences, physical sciences, computer science and technology, and engineering. Once again, we first examine models with only the main effect of social relevance, and then include an interaction term between social relevance and gender to address whether perceptions of the social relevance of science matter more for girls' expectations to major in specific fields of STEM. Throughout, we utilize clustered models with robust standard errors that take into account the nesting of students within schools.[5]

4. Results

4.1. Expectations to Major in Any STEM Field

The first part of our analysis examines whether students' perceptions of the social relevance of science shape expectations to major in any STEM field and whether these perceptions may be especially powerful for girls. The results are included in Table 2, below. Consistent with prior research [11,44,45] our baseline model (model 1) shows that girls are less likely than boys to intend to major in STEM fields in the aggregate (consistent with Figure 1), while those from higher social class background (as captured through the proxy of books in the home), and students who are born outside the U.S. are also significantly more likely to expect to major in STEM (although the p-value for the former is 0.06 indicating a marginally significant effect). Students with higher levels of science achievement are also significantly more likely to expect to major in a STEM field (although the effect is borderline

4 In analyses not shown here, we also included a measure of students' science self-efficacy or self-confidence, as prior research finds that this positively predicts STEM outcomes [9]. However, because the survey only included one item to measure efficacy ("I usually do well in science"), and it did not significantly predict students' plans to major in STEM net of their science affect, nor did it alter the impact the results shown here, we chose not to include it in the final models.

5 Multi-level random effects models yielded extremely similar results, but the variation across schools was not statistically significant.

at $p = 0.09$), as are those with higher levels of science affect. In model 2, we find that students who perceive science as more socially relevant are in turn more likely to expect to major in STEM. This effect is only borderline significant (B = 0.42, $p = 0.09$), and appears weaker than the measure for science affect. Specifically, in model 2, a one standard deviation increase in a students' perceptions of the social relevance of science is associated with an increase of 0.03 in the probability of expecting to major in STEM, while a one standard deviation increase in science affect results in a predicted increase of 0.07.[6] As expected, adding perceptions of social relevance to the model does not diminish the gender gap in expectations as boys and girls have similar means.

Table 2. Results from logistic regression models predicting expectations to major in any STEM field (Coefficients with standard errors in parentheses) (N = 935).

	M1		M2		M3	
	Coef	***p***	**Coef**	***p***	**Coef**	***p***
Focal Independent Variable						
Perceived social relevance			0.42 (0.25)	~	−0.14 (0.37)	
Interaction Effects						
Female * Relevance					0.93 (0.46)	*
Female	−0.88 (0.14)	***	−0.91 (0.14)	***	−1.22 (0.22)	***
Control Variables						
Social background						
Race/ethnicity						
Black	0.10 (0.30)		0.08 (0.30)		0.09 (0.30)	
Hispanic	0.25 (0.26)		0.27 (0.26)		0.29 (0.26)	
Born outside of the U.S.	0.74 (0.21)	***	0.75 (0.21)	***	0.76 (0.21)	***
Books in the home	0.31 (0.16)	~	0.31 (0.16)	~	0.32 (0.16)	*
Science achievement	0.17 (0.10)	~	0.14 (0.10)		0.14 (0.10)	
Science affect	0.89 (0.18)	***	0.76 (0.20)	***	0.80 (0.20)	***
Constant	0.17 (0.29)		−0.04 (0.30)		0.11 (0.31)	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ~ $p < 0.10$, two-tailed test.

Model 3 adds an interaction between gender and perceived social relevance to the set of variables previously included in Model 2. The interaction term is positive and statistically significant, indicating a greater effect of relevance for girls. Additionally, the main effect is now negative, smaller, and not significant.

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[6] Throughout, the estimated increases in probability of majoring in STEM are calculated using the *margins* post-estimation command in Stata.

To better illustrate the gendered patterns from model 3 of Table 2, in Figure 2 we show the predicted probabilities of expecting to major in STEM for boys and girls as a function of their perceptions of the social relevance of science. All other variables in the model are held to the mean. We see that as perceptions of the social relevance of science increase, girls' probabilities of expecting to major in STEM increase substantially, though boys' probabilities remain relatively flat. Put differently, while boys' average probability of having expectations to major in a STEM field is quite high (around 0.7), it is virtually insensitive to their perceptions of science. However, for girls, perceiving science as more socially relevant is associated with a much higher likelihood intending to major in STEM. Thus, students' perceptions of the social relevance of science clearly operate in notably gendered ways in shaping plans to major in STEM.

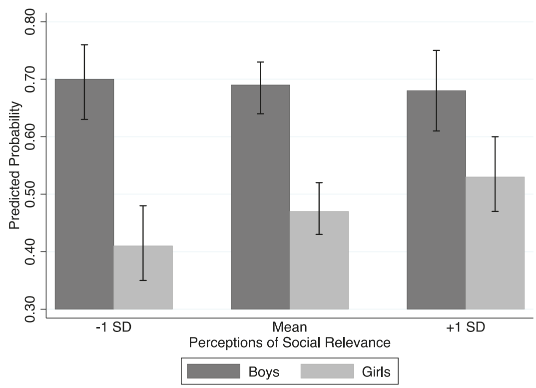

Figure 2. Predicted probability of expecting to major in STEM by perceptions of social relevance and gender.

4.2. Field-Specific STEM Expectations

To address the second part of our research agenda, we now examine whether perceptions of the social relevance of science shape expectations to major in specific fields within STEM and whether and how this may differ by gender. In Table 3, we proceed with the same series of covariates in our models as in Table 2. However, this analysis models students' likelihood of expecting to major in the biological sciences ([A] models, leftmost section of table), the physical sciences ([B], second section from the left), computer science ([C], second section from the right), and engineering ([D], rightmost section).

Turning first to expectations to major in the biological sciences, the baseline model (A1) shows that students with higher science affect as well as those born outside the U.S. and those with more books at home are more likely to expect to major in the biological sciences. Model A1 also shows that girls are significantly more likely than boys to intend to major in the biological sciences. In the second model (A2) we see that students who perceive science as more socially relevant are significantly more likely to expect to major in the biological sciences. Finally, in model A3, the interaction between gender and social relevance is positive and marginally significant ($p = 0.08$), while the main effect is greatly diminished and no longer statistically significant. Thus the pattern of results for the biological sciences generally follows that observed in Table 2 for any STEM field. Specifically, calculating predicted probabilities (with other variables held to the mean) reveals that as girls' perceptions of social relevance increase from one standard deviation below the mean to one standard deviation above the mean, their probability of declaring a biological science major increases from 0.13 to 0.24, while boys' predicted probabilities (non-significantly) increase from 0.13 to 0.15.

Table 3. Results from Logistic Regression Models Predicting Expectations to Major in Specific STEM Fields (Coefficients with standard errors in parentheses) (N = 935).

	Biological Sciences						Physical Sciences						Computer Science						Engineering					
	A1		A2		A3		B1		B2		B3		C1		C2		C3		D1		D2		D3	
	Coef	***p***	**Coef**	***p***	**Coef**	***p***	**Coef**	***p***	**Coef**	***p***	**Coef**	***p***	**Coef**	***p***	**Coef**	***p***	**Coef**	***p***	**Coef**	***p***	**Coef**	***p***	**Coef**	***p***
Focal Independent Variable																								
Perceived social relevance			0.82 (0.31)	**	0.23 (0.46)				0.75 (0.31)	*	0.03 (0.44)				0.47 (0.27)	~	0.46 (0.35)				0.31 (0.26)		−0.18 (0.34)	
Interaction Effects																								
Female * Relevance					0.99 (0.56)	~					1.29 (0.56)	*					0.02 (0.47)						1.01 (0.46)	*
Female	0.36 (0.18)	*	0.34 (0.18)	~	−0.09 (0.30)		0.11 (0.18)		0.09 (0.18)		−0.47 (0.30)		−0.66 (0.15)	***	−0.68 (0.15)	***	−0.69 (0.24)	**	−1.39 (0.15)	***	−1.41 (0.15)	***	−1.79 (0.23)	***
Control Variables																								
Social background																								
Race/ethnicity																								
Black	0.22 (0.36)		0.19 (0.36)		0.20 (0.36)		−0.14 (0.36)		−0.17 (0.36)		−0.16 (0.36)		0.29 (0.34)		0.27 (0.34)		0.27 (0.34)		−0.40 (0.31)		−0.42 (0.31)		−0.40 (0.30)	
Hispanic	0.24 (0.31)		0.32 (0.32)		0.34 (0.32)		−0.04 (0.31)		0.03 (0.31)		0.05 (0.32)		0.45 (0.30)		0.48 (0.31)		0.48 (0.31)		−0.17 (0.27)		−0.15 (0.27)		−0.12 (0.27)	
Born outside of the U.S.	0.68 (0.22)	**	0.69 (0.22)	**	0.70 (0.22)	***	0.54 (0.22)	*	0.55 (0.23)	*	0.57 (0.23)	*	0.22 (0.20)		0.23 (0.20)		0.23 (0.20)		0.49 (0.20)	*	0.49 (0.20)	*	0.50 (0.20)	*
Books in the home	0.53 (0.19)	**	0.54 (0.19)	**	0.55 (0.20)	**	0.46 (0.20)	*	0.48 (0.20)	*	0.49 (0.20)	*	−0.05 (0.17)		−0.04 (0.17)		−0.04 (0.17)		0.12 (0.17)		0.12 (0.17)		0.13 (0.17)	
Science achievement	0.01 (0.12)		−0.05 (0.13)		−0.05 (0.13)		−0.12 (0.12)		−0.18 (0.13)		−0.18 (0.13)		−0.06 (0.11)		−0.09 (0.11)		−0.09 (0.11)		0.23 (0.10)	*	0.21 (0.11)	~	0.21 (0.11)	*
Science affect	1.08 (0.21)	***	0.85 (0.23)	***	0.88 (0.23)	***	1.33 (0.21)	***	1.12 (0.23)	***	1.16 (0.23)	***	0.54 (0.19)	**	0.39 (0.20)	~	0.39 (0.20)	~	0.38 (0.18)	*	0.28 (0.20)		0.31 (0.20)	
Constant	−2.70 (0.37)	***	−2.99 (0.39)	***	−2.78 (0.40)	***	−2.36 (0.36)	***	−2.62 (0.38)	***	−2.36 (0.39)	***	−1.21 (0.33)	***	−1.34 (0.34)	***	−1.34 (0.35)	***	0.06 (0.29)		−0.02 (0.30)		0.11 (0.31)	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ~ $p < 0.10$, two-tailed test.

Moving to the next set of models within Table 3, we now consider the role of social relevance in shaping expectations to major in the physical sciences. In the baseline model we see that those born outside the U.S., those with more books in the home, and those with a more positive science affect are more likely to expect to major in the physical sciences. Also consistent with Figure 1, we see that gender is not a significant predictor of expectations of majoring in the physical sciences. In model B2, we see a positive and significant effect of perceptions of the social relevance of science. Yet with the inclusion of the interaction between gender and relevance, we once again see that this positive association is driven by girls, as the main effect moves very close to zero and is not significant, indicating no discernible impact for boys, while the interaction is positive and statistically significant. Specifically, as girls' perceptions of social relevance increase from one standard deviation below the mean to one standard deviation above the mean, their probability of declaring a physical science major increases from 0.11 to 0.22, while boys' predicted probabilities remain at around 0.15.

The next portion of Table 3 examines the role of social relevance in shaping expectations to major in computer science. As expected, the baseline model (C1) shows that girls are much less likely to expect to major in computer science, while those with higher science affect are more likely. Model 2 reveals a small, positive, and marginally significant effect ($p = 0.08$) of perceptions of social relevance. Unlike previous models, the coefficient measuring the interaction between gender and social relevance in the third model is close to zero and not statistically significant. With its inclusion, the main effect remains virtually the same in size but is no longer statistically significant.

Finally, the rightmost models of Table 3 consider the role of social relevance in shaping expectations to major in engineering. The baseline model (D1) shows that girls are much less likely to expect to major in engineering compared to boys, while those born outside the U.S., high science achievers, and those with higher levels of science affect are significantly more likely than their peers to plan to major in engineering. Including perceptions of science relevance in model D2 explains away the positive effect of science affect found in D1, yet social relevance does not significantly predict students' expectations to major in engineering. Yet with the inclusion of the interaction term in model D3, which is positive and statistically significant, it appears that the absence of a main effect obscures the positive impact of perceptions of social relevance that exists uniquely for girls. Specifically, as girls' perceptions of social relevance increase from one standard deviation below the mean to one standard deviation above the mean, their probability of declaring an engineering major rises from 0.17 to 0.26, while boys' predicted probabilities hover at around 0.5. Taken together, consistent with the biological and physical sciences but in contrast to computer science, girls alone appear more likely to plan to major in engineering when they perceive science to be socially relevant.

5. Discussion

Despite decades of scholarly attention on the topic of what draws students to STEM fields, there is a lack of empirical literature that focuses explicit attention on how young people perceive science, and how such perceptions may be directly linked to their future plans to pursue STEM fields. This study attempts to address this by drawing on two different areas of research that essentially present competing ideas about whose intentions may be shaped by views of science as socially relevant. Specifically, gender scholars hold that gender stereotypes guide girls toward fields that are viewed as having the broad capacity to help others, improve life, and make a difference in the world. From this perspective, girls who perceive science as socially relevant may be more likely to pursue these fields as a way of fulfilling the normative feminine role dictated by prevailing cultural beliefs about gender, while boys' decisions to enter STEM are likely unaffected by perceptions of social relevance, as normative masculine roles do not include placing a priority on such things. By contrast, scholars from within science education would argue that perceiving science as socially relevant encourages STEM expectations similarly among both girls and boys, as students are more likely to want to continue studying a subject that has meaning and importance outside of school walls. This study examines this issue directly by examining whether perceptions of social relevance guide expectations to major in

STEM among adolescents. In doing so, we examine not only the role of social relevance in guiding interest in STEM in general, but also the extent to which social relevance guides students toward specific majors within STEM—namely, the biological and physical sciences, computer science, and engineering. Because students' expectations as ninth graders will guide their decision-making and academic preparation for college, these foreshadow gendered pathways into STEM in higher education and ultimately, the labor force [6,46].

In examining how perceptions of the social relevance of science shape expectations to major in STEM at the start of high school, we found that viewing science as socially relevant clearly increases the likelihood that students will intend to major in STEM in ways that are gendered. Consistent with the view offered by gender theorists, we found highly gendered patterns in how social relevance guides students' intentions to pursue STEM majors in the aggregate. As seen in Table 2 (and the associated Figure 2), perceiving science as more socially relevant is associated with a statistically significant and substantial increase in girls' expectations to major in a STEM field, while boys' expectations are not moved in response to such views. Subsequent field-specific analyses reveal that this same gendered pattern appears in three of the four STEM fields considered, specifically, the biological sciences, physical sciences, and engineering. Thus we find that in our sample, perceptions of social relevance are an important predictor of adolescent girls' intentions to enter STEM postsecondary fields where women are currently well-represented (the biological sciences, and to a lesser extent, the physical sciences) as well as in engineering, a field that remains highly male-dominated [21]. Indeed, this suggests that recent efforts, such as ad campaigns by organizations such as Exxon/Mobil that highlight the power of engineering to change the world for the better, could perhaps move the needle towards gender equity [47].

By contrast, our results for computer science are not quite as clear. We find a borderline significant main effect of the perceived social relevance of science, and no evidence of a gender interaction. Thus on the one hand, the results might be interpreted as consistent with science education researchers who suggest that all students benefit when they view science as relevant and powerful for solving problems outside of school walls. In practice, this insight offers a potentially useful avenue for increasing participation in computer science by linking it to solving real-world problems in the minds of both male and female adolescents. Yet, we also note that the effect we observe is relatively small, and thus such perceptions may do little on a practical scale to move more girls into a field where women are so grossly under-represented.[7]

6. Conclusion

Though the specific focus of our paper was on examining the gendered impact of perceptions of social relevance, our findings also speak to larger conversations about gender gaps in STEM participation. Specifically, we found that a majority of ninth-grade girls in our sample (54%, compared with 32% of boys) have already expressed a disinterest in pursuing any STEM major. Moreover, the gendered patterns we observe in Figure 1 regarding future intentions in specific STEM fields largely mirror current patterns of gender representation in postsecondary education at the national level as well as within the labor force [47]. Thus our results underscore the powerful role of gender in shaping students' plans long before the transition to college, as well as hint that perhaps we should not anticipate that younger cohorts will play a role in changing patterns of gender segregation. Yet at the same time we note one potentially positive sign; perhaps reflecting changes in interest in technology among younger cohorts, computer science and engineering were the most popular STEM majors for both girls and boys in our sample.

[7] Specifically, as students increase from one standard deviation below the mean to one standard deviation above the mean on the social relevance scale, their predicted probability of expecting to major in computer science increases from 0.24 to 0.29.

As with any study, there are several limitations and other questions that arise that cannot be addressed by the present study. First, because this study focuses on predominantly Hispanic high school students in one large, urban school district, it is not possible to say how the patterns observed here would compare to other contexts. Future research could address this, as well as whether patterns might be similar or different among both younger and older student populations. Moreover, we looked for but did not find racial/ethnic differences in how social relevance predicted students' STEM intentions.[8] Moving forward, it would be informative to consider these dynamics at the intersection of race/ethnicity and gender, which unfortunately we could not explore due to sample size. Furthermore, specific survey items examining how students view the social relevance of specific STEM fields, such as engineering, would be even more informative than the general questions utilized in this study. Current efforts to address such issues are hampered by the scarcity of data that is both large in scope and detailed in its STEM focus. Yet, by demonstrating that perceptions of social relevance may help guide more girls into STEM fields, future scholars can build on the contribution begun here.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Zero-order correlations between variables.

	Expects to Major in STEM	**Biological Sciences**	**Physical Sciences**	**Computer Science**	**Engineering**	**Female**	**Black**	**Hispanic**	**Born Outside of the U.S.**	**Books in the Home**	**Science Achievement**	**Science Affect**	**Perceived Social Relevance**
Expects to major in STEM	1.00												
Biological sciences	0.41	1.00											
Physical sciences	0.41	0.46	1.00										
Computer science	0.54	0.13	0.19	1.00									
Engineering	0.66	0.07	0.18	0.34	1.00								
Female	−0.22	0.05	0.00	−0.16	−0.32	1.00							
Black	−0.02	0.00	−0.01	−0.02	−0.04	−0.01	1.00						
Hispanic	0.02	−0.01	−0.02	0.06	0.01	−0.02	−0.75	1.00					
Born outside of the U.S.	0.11	0.10	0.07	0.04	0.08	−0.03	−0.07	0.07	1.00				
Books in the home	0.07	0.10	0.08	−0.04	0.04	0.04	0.09	−0.31	0.01	1.00			
Science achievement	0.07	0.03	0.01	−0.03	0.10	−0.02	−0.06	−0.15	−0.07	0.31	1.00		
Science affect	0.18	0.17	0.21	0.10	0.10	−0.08	−0.01	−0.02	−0.02	0.07	0.10	1.00	
Perceived social relevance	0.11	0.15	0.15	0.07	0.06	0.03	0.11	−0.17	−0.04	0.11	0.21	0.40	1.00

[8] It is important to note that national studies have found that Hispanic as well as Black adolescents exhibit similar levels of interest in STEM fields as their white peers, and conditional on college matriculation, are as likely to enter STEM majors in college [48].

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Science Possible Selves and the Desire to be a Scientist: Mindsets, Gender Bias, and Confidence during Early Adolescence

Patricia Wonch Hill [1,*], Julia McQuillan [2], Eli Talbert [3], Amy Spiegel [1], G. Robin Gauthier [2] and Judy Diamond [4]

1 Social and Behavioral Sciences Research Consortium, University of Nebraska-Lincoln, Lincoln, NE 68588-0866, USA; aspiegel1@unl.edu
2 Department of Sociology, University of Nebraska-Lincoln, Lincoln, NE 68588-0324, USA; jmcquillan2@unl.edu (J.M.); gertrude.gauthier@gmail.com (G.R.G.)
3 Department of Psychology in Education, University of Pittsburgh, Pittsburgh, PA 15260, USA; ejt26@pitt.edu
4 University of Nebraska State Museum, University of Nebraska-Lincoln, Lincoln, NE 68588-0374, USA; jdiamond1@unl.edu
* Correspondence: phill3@unl.edu

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Abstract: In the United States, gender gaps in science interest widen during the middle school years. Recent research on adults shows that gender gaps in some academic fields are associated with mindsets about ability and gender-science biases. In a sample of 529 students in a U.S. middle school, we assess how explicit boy-science bias, science confidence, science possible self (belief in being able to become a scientist), and desire to be a scientist vary by gender. Guided by theories and prior research, we use a series of multivariate logistic regression models to examine the relationships between mindsets about ability and these variables. We control for self-reported science grades, social capital, and race/ethnic minority status. Results show that seeing academic ability as innate ("fixed mindsets") is associated with boy-science bias, and that younger girls have less boy-science bias than older girls. Fixed mindsets and boy-science bias are both negatively associated with a science possible self; science confidence is positively associated with a science possible self. In the final model, high science confident and having a science possible self are positively associated with a desire to be a scientist. Facilitating growth mindsets and countering boy-science bias in middle school may be fruitful interventions for widening participation in science careers.

Keywords: adolescence; bias; gender; identity; mindsets; science; science careers

1. Introduction

The gender gap in science persists in many fields despite increases in the participation of women in the paid workforce and 4-year colleges and graduate and professional schools (Ceci et al. 2014). Explanations for this gap include a number of individual, interactional, and institutional mechanisms including gendered socialization, implicit biases, stereotypes, and discrimination (Cheryan et al. 2015; Grunspan et al. 2016; Hill et al. 2010; Moss-Racusin et al. 2012; Xie and Shauman 2003). Evidence suggests that in the United States, in elementary school, both boys and girls have similar levels of interest in science, but by middle school, interest in science among girls has diminished (Andre et al. 1999; Blue and Gann 2008). This disproportionate decline in science interest for adolescent girls compared to boys cannot be due to differences in academic success; on average girls have equivalent or better grades in math and science than boys at every age (Voyer and Voyer 2014).

One compelling explanation for the science interest gap between boys and girls is the complex social, psychological, and developmental processes that happen during adolescence. In particular, there is evidence that gender identity becomes more salient during adolescence (Galambos et al. 1990). For girls compared to boys, greater gender identity salience can result in lower self-esteem, and reduced confidence across many social and psychological domains (Orenstein 2013), including confidence in science and math (Heaverlo et al. 2013). Biased self-assessments may also emerge from implicit and explicit biases in the U.S. and other western European countries where there is a widely held cultural belief that boys are better at science (and math) than girls (Nosek et al. 2009; Cai et al. 2016). Because of the bias towards boys as science kinds of people, girls may not perceive their gender identity as compatible with a science identity (Nosek et al. 2002; Nosek and Smyth 2011). Considerable research has been focused on how to close the "science identity gap" for girls, as well as other underrepresented minorities in science (Archer et al. 2010, 2012, 2013; Barton et al. 2013; Kozoll and Osborne 2004).

The challenges that some girls experience combining "girl" and "science" identities may be influenced by whether or not valued abilities are viewed as innate or attained through effort (Blackwell et al. 2007; Levy et al. 1998). Indeed, research in adult populations show that at least some of the science gender gap can be explained by mindsets about intelligence (whether it is fixed or whether it can be developed through effort), and gendered assumptions about boys' presumed "innate brilliance" compared to girls' presumed "hard work" (Leslie et al. 2015).

The extent to which stereotypes about girls and science, and mindsets about intelligence influencing science identity, warrants further investigation. Because science career aspirations begin forming in early adolescence (Tai et al. 2006), one way that researchers have explored the relationship between science identity and science career aspirations is by assessing youth science possible selves (Packard and Nguyen 2003), or the perception that they may someday become a scientist (Oyserman et al. 2006). There are no studies of middle school aged youth that have simultaneously included measures of mindsets, boy-science bias, science confidence, and science possible selves, yet there are reasons to expect that each of these concepts contributes to the desire to be a scientist.

In this study, we assess science possible selves, and the desire to be a scientist in a sample of 529 adolescents in a U.S. Title I (high poverty) middle school. Using developmental theories about gender identity, mindsets, and science possible selves, we assess multiple hypotheses about how gender, grade level, and mindsets are associated with boy-science bias, science confidence, science possible selves, and the desire for a science career.

1.1. Gender Identity in Early Adolescence

Adolescence is an important time in the life course. Children begin the social and physical transition to adulthood, and in so doing explore, affirm, or cast aside identities (Eccles et al. 1997; Eckert 1989; Eder 1995). Gendered identities are also "under construction" in early adolescence, when youth are "trying on gender" and other identities as they imagine futures compatible with salient identities, particularly related to gender (Williams 2002).

According to the gender intensification hypothesis, gender identities become more relevant in adolescence, and the intensification contributes to lower self-esteem and reduced mental health for girls (Galambos 2004; Pettitt 2004). Similarly, confidence drops more for girls than boys during adolescence in many areas of life, including in science and math (Orenstein 2013). In school contexts, gender intensification may be explicitly or implicitly endorsed by peers and significant adults (Eder 1995; Adler et al. 1992; Thorne 1993). A classic ethnographic study by Eder (1995) showed that middle school is a time when girls more often become objectified and sexualized, and where social status for girls is often based on physical appearance, relationships with boys, and friendships with girls, compared to an emphasis on achievement for boys (Eder 1995). Bullying is more common during middle school than elementary and high school (Olweus 2013), and sexual harassment of adolescent girls is widespread (Leaper and Brown 2008).

In addition to the overt sexualization and objectification of many girls during puberty, many girls also face academic sexism (Archer et al. 2013; Banchefsky et al. 2016). Academic sexism involves actions that discourage girls from participating in areas deemed as "male", such as science, math, and computers (Leaper and Brown 2014). In a study of 600 girls, Leaper and Brown (2008) found that 52% of the sample reported some form of academic sexism related to math and science, with the majority perpetrated by peers, but also reportedly from parents. If being desirable, feminine, and sexy is perceived as incompatible with interest and achievement in science, girls may distance themselves from science and also fail to form friendships around science (Archer et al. 2013; Banchefsky et al. 2016). Peer influence can increase or decrease academic achievement, positive identities, and overall well-being (Crosnoe and McNeely 2008; Crosnoe et al. 2008; Leaper et al. 2012). Friendship groups are highly segregated by gender (Shrum et al. 1988). Altogether, these social and cognitive processes and biases may influence science aspirations differently for boys and girls (Gauthier et al. 2017).

1.2. Mindsets and Gender Stereotypes

There is compelling evidence that implicit theories about the malleability of traits (i.e., mindsets) can foster or inhibit the development of possible future selves (Levy et al. 1998; Levy and Dweck 1999; Stroessner and Dweck 2015). According to Dweck (2006), people with a growth mindset believe that abilities can be developed. With a fixed mindset, people believe that intelligence or talent are simply fixed traits that they were either born with, or not. People with fixed mindsets focus on documenting intelligence or talent instead of developing intelligence and talents (Dweck 2006). There is evidence that a fixed mindset might emerge from fundamental cognitive processes that help people make sense about the world, but can also lead to errors about the world (Bigler and Liben 1993).

The process of overly simplistic categorizing can lead to inflating differences between groups and ignoring variation within groups, resulting in stereotyping and biases (Master et al. 2012). One common type of error in reasoning that leads to gender stereotypes is called psychological essentialism, or the belief that people naturally possess certain traits based on group characteristics (Stroessner and Dweck 2015; Cimpian and Salomon 2014). Gender essentialism is the belief that differences between boys and girls are natural or innate (based in biology) and that they cannot be changed (Eidson and Coley 2014). This is because if boys are seen as naturally or effortlessly brilliant, and science requires brilliance, then fixed mindsets about intelligence and essentialist mindsets about gender may lead to a science-gender bias favoring boys, and disfavoring girls.

For girls, a boy-science bias might contribute to the pattern of more girls than boys becoming disinterested in science, and may result in a lower likelihood of having a science possible self and/or a desire to be a scientist in middle school for girls more than boys. Conversely, for boys, in group-favoritism (favoring those who belong to your social group) and intergroup biases (disfavoring those not in your social group), may translate into a boost from boy-science bias, resulting in a stereotype lift effect for science possible selves and a desire to be a scientist (Walton and Cohen 2003; Tajfel and Turner 2004).

Although many people perceive that gender stereotypes and biases have disappeared, recent research (2014) shows that there are similar levels of gender stereotypes among contemporary college age youth as in 1980 (Haines et al. 2016). Even though there is evidence that actual explicit gender stereotypes persist, they are likely underreported in surveys due to social desirability.

1.3. Science Confidence and Science Possible Selves

In the United States there is a strong belief that youth can choose any career; therefore it can be popular to blame under-representation of women in science and engineering professions on personal preference rather than social structural inequality (Rosenbloom et al. 2008). Charles and Bradley (2009) argue that the higher standard of living in the United States, combined with implicit gender biases about science, contribute to many youth "indulging our gendered selves" when 'choosing' career paths. Research suggests, however, that more than simply reflecting an individual's abilities, career paths are also shaped by social identities and cultural beliefs about who we are, and where we fit in, perhaps even more than what we are good at (Correll 2001, 2004; Cech 2013).

Our identity, or how we see our self, is a social construction; it is a product of shared social interactions and cognitive processes related to social and self-categorizations (Tajfel and Turner 2004; Burke and Stets 2009; Turner et al. 1987). These conceptions of the self are dynamic and are based on our experiences of the social world, including our self-appraisals and reflected appraisal from significant others (e.g., parents, teachers, and peers) (Bouchey and Harter 2005; Gunderson et al. 2012). Our identities are not socially constructed in a vacuum, but are formed within larger social structures and within social institutions (like schools) that are also gendered (Charles and Bradley 2009; Acker and Oatley 1993; Connell 2014; Ridgeway 2009; Risman 2004). Therefore, given these social and institutional contexts, these self-appraisals may be biased or inaccurate and may vary by gender (Correll 2001). At the college level, women's biased self-assessments and perceptions of a lack of "fit" can impact women's persistence in some Science, Technology, Engineering, and Math (STEM) fields, (e.g., engineering and computer science) (Cech 2013; Cech et al. 2011; Master et al. 2015). In international studies on adolescent education and achievement, for youth in some high achieving countries, researchers find a negative relationship between student achievement and self-concept; the better students do, the lower they rate their own abilities (Wilkins 2004). In a national study of eighth grade girls in the U.S., researchers found that these biased self-assessments in science are more likely for girls than for boys (Riegle-Crumb et al. 2011); this phenomenon is sometimes referred to as the "confidence gap" (Orenstein 2013).

Identities shape our actions and choices, plus they influence our commitment to pursuing future goals. Therefore, these emerging identities in adolescence are important for many long-term social, emotional, and career outcomes (Eccles et al. 1997; Schwartz et al. 2015). Adolescents make choices about who they are friends with, what activities they pursue, and in high school, what classes to take, in order to validate their identities and to maintain their self-esteem (Barton et al. 2013; Barber et al. 2005; Cast and Burke 2002). Adolescence is also a time when many youth are asked what they want to be when they grow up. Images of who youth might be in the future are referred to as possible selves (Markus and Nurius 1986). Possible selves can be either negative or positive and a possible self that a person finds plausible will affect their current behavior and choices (Oyserman et al. 2006).

A science possible self, or the belief that you might be able to become a scientist someday, is one outcome of emergent science identities during adolescence (Buday et al. 2012). A student who believes that they might be a successful scientist in the future is more likely to express interest in scientific endeavors, excel in science classes, and to form friendships around science activities (Robnett and Leaper 2013). Indeed, the social aspect of science is often overlooked, even though we know that social interactions, validation, and recognition are important for identity (Carlone and Johnson 2007). In a longitudinal study of 41 high school girls who transitioned into college, researchers found social support and mentoring to be important predictors of science career-related possible selves (Packard and Nguyen 2003). Lips (2004) found that college and high school age women were much less likely to have science possible selves compared to men, and that college-aged women saw even less science possibility than high school women, indicating that science pathways constrict more for women than men over time (Lips 2004). In a more recent study, Buday, Stake, and Peterson (2012) found that for both boys and girls, social support was crucial to having a high science possible self, but did not find a gender differences in science possible selves (Buday et al. 2012).

The aforementioned studies all explore science possible selves, but had small sample sizes and were not representative of a general population of students. In addition, these studies have consisted of youth who had been identified as having science and math aptitude and been enrolled in specific science focused programs based on that aptitude and interest. In addition, no studies simultaneously examine mindsets, boy-science bias, science confidence, science possible selves, and the desire to be a scientist. Middle school is a time for early career exploration when science career preferences may emerge, strengthen, or for some, diminish (Tai et al. 2006; Dabney et al. 2015, 2012). Clearly, we need more investigation of identity formation, science possible selves, and youth trajectories in science among boys and girls to understand how science possible selves may be associated with science career aspirations more broadly (Buday et al. 2012).

1.4. Current Study

Our goal is to add to the emerging understanding of the origins of gender gaps in science interest by modeling the sources of the gap using a series of multiple logistic regression models. We use a sample of 529 middle school youth in a midsized Midwestern middle school to first assess how middle school youth differ on key focal science attitudes and beliefs by gender. We then assess whether gender, grade level, or mindsets are associated with having a boy-science bias after adjusting for social capital and racial/ethnic minority status. Next, we assess the extent to which gender, grade level, mindsets, and boy-science bias are associated with science confidence after controlling for self-reported grades, social capital, and racial/ethnic minority status. Theories of stereotype formation indicate that biases among boys and girls may be associated with boy-science bias and science confidence differently by age, therefore we estimate interaction by gender and grade level. In addition, theories about in-group bias and stereotype lift suggest that the association between boy-science bias and science possible selves should be gender specific, therefore we estimate an interaction by gender.

1.5. Hypotheses

H1: Boys will have higher boy-science bias, science confidence, science possible self, and a desire to be a scientist than girls. Boys and girls will not differ on science grades, fixed mindsets, or essentialist mindsets.

H2: For all youth, including both boys and girls, fixed or essentialist mindsets will be associated with having a boy-science bias, after controlling for minority status and social capital variables.

H3a: For girls, but not boys, boy-science bias will vary by grade level; girls in lower grade levels will have less boy-science bias than girls in higher grade levels, after adjusting for mindsets, and controlling for self-reported grades, minority status, and social capital variables.

H3b: For girls, but not boys, we expect that science confidence will vary by grade level; girls in lower grade levels will have higher science confidence than girls in higher grade levels, after adjusting for mindsets, boy-science bias, and controlling for self-reported grades, minority status, and social capital variables.

H4a: For girls, but not boys, boy-science bias will be associated with a lower likelihood of a science possible self, after adjusting for mindsets, science confidence, and controlling for self-reported grades, minority status, and social capital variables.

H4b: For boys, but not girls, boy-science bias will be associated with a higher likelihood of a science possible self, after adjusting for mindsets, science confidence, and controlling for self-reported grades, minority status, and social capital variables.

H5: For all youth, higher science confidence and higher science possible self will be associated with a desire to be a scientist, after adjusting for mindsets, boy-science bias, and controlling for self-reported grades, minority status, and social capital variables.

2. Materials and Methods

We used SPSS version 22, and *t*-tests and chi-square tests to compare means and proportions for all theoretical variables by gender. Next, we show correlations between variables using a Pearson's *r* correlation to assess for multicollinearity and to assess bivariate relationships between key theoretical variables. Finally, we use multivariate logistic regression to estimate associations with boy-science bias, science confidence, science possible selves, and the desire to be a scientist. Because of important prior work on the underrepresentation of some race/ethnic minority groups and elitism in science, we control for race/ethnic minority status and social capital in all models (Catsambis 1995; Hazari et al. 2013).

2.1. Participants

The data collected for this study are from Wave III of the *Study of Science Identity in Middle School*, (collected in January 2015). All sixth, seventh, and eighth grade students enrolled in science classes at a Title I (high poverty) Middle School in a mid-sized Midwestern city were asked to participate in the survey. All parents or guardians of potential participants were notified of the opportunity to participate in the survey with an automated phone call and email, and were provided a form to opt their child out of the study if desired. These forms were available in English, Spanish, Vietnamese, and Arabic. Of the 645 students at the school, 95% (610) were enrolled in a science class. Those who were not were either suspended or were placed in a low proficiency English Language Learner (ELL) classroom instead of a science classroom. Of those eligible to participate, 87% (533) chose to participate in the survey, 529 of which we have complete data for all analytic variables. Institutional Review Board (IRB) approval was obtained for this study prior to participation.

Because this is a study of a single school, we use caution in generalizing the findings. This school is demographically diverse. A high proportion of youth come from racial/ethnic minority groups (69.9%), and a large proportion of youth receive free and reduced lunch (78%). Not only can we not generalize, the gender dynamics in this school may be different than in schools with higher socio-economic status (SES) and that are less diverse (Armstrong et al. 2014; Hamilton and Armstrong 2009). Even with this limitation, this research can provide insights into gender, identity development, and science career aspirations during middle school years, and suggestions for valuable further exploration of this critical developmental time.

2.2. Measures

To assess the extent to which youth have a desire to be a scientist when they grew up, we asked them, "How much, if at all, do you want to be a scientist?" (1 = A lot, 2 = Some, 3 = A little, 4 = Not at all). We dichotomized this variable so that wanting to be a scientist "A lot" = 1 (7.3%) and all other categories have a value of 0.

We operationalized science possible selves in order to take into account that many youth in early adolescence might see a science career path as a possibility, but might favor another career path more (Archer et al. 2014). For middle school students, asking how much they want to be a scientist might not capture their perception of how open a science path is to them. For example, even students who want to be a famous musician, actor, or athlete might still see science as a possible path. Therefore, we measure a science possible self with the following item: "For this question, let's pretend you want to be a scientist when you grow up. Which of the following best describes you?" (1 = I could become a scientist, 2 = I might be able to become a scientist, 3 = I probably could not become a scientist, 4 = I could not become a scientist, and 5 = I don't know). We dichotomized this variable so that those that reported "I could become a scientist" have a value of 1 (23.1%), and all other categories are a zero.

To measure science confidence, students were asked, 'How good are you at science?' (1 = Poor, 2 = Fair, 3 = Good, 4 = Excellent). We dichotomized this variable so that those who report they are "Excellent" at science = 1 (20.2%).

To measure explicit boy-science bias we asked the question "Do you think boys or girls are better at science?" The response categories are similar to a measure of explicit science and math gender stereotypes used in other studies that provide a category in which boys and girls are the same, indicating no stereotype (Nosek et al. 2009, 2002; Cai et al. 2016). We dichotomized the responses into those who think girls are better at science, and those think boys and girls are the same at science (boy-science bias = 0), compared to those who think that boys are better at science (more boy-science bias = 1). Our coding reflects the dominant cultural stereotype in the U.S.; that boys are better at science than girls. Approximately 16% of all students report that boys are either a little or a lot better at science than girls.

We assess the extent to which youth have fixed mindsets based on an item from Dweck (Blackwell et al. 2007) that we modified for readability based on the young age of our sample. Students were asked how much they agree with the following statement, "You can learn new things, but you can't really change how smart you are." This variable had a range from 1–5 where 1 = Strongly Disagree, 5 = Strongly Agree. The mean is 2.5 (S.D. = 0.05). We also developed a measure guided by the theory of mindsets to assess essentialist mindsets, "Some people are just naturally good at things (like sports, science or music) and will never have to work hard at them." This variable had a range from 1–5 where 1 = Strongly Disagree, 5 = Strongly Agree. The mean is 2.7 (S.D. = 0.06)

Science grades were self-reported; we asked students "What grades do you usually get in science classes?" (1 = Mostly below C's, 2 = Mostly C's, 3 = Mostly B's and C's, 4 = A mix of A's, B's, and C's, 5 = Mostly B's, 6 = Mostly A's and B's, 7 = Mostly A's). The mean is 5 (S.D. = 0.07).

We measure social capital using two variables, the number of books in the home and college expectations. We asked students, "About how many books do you have in your home?" (1 = 0–10 books, 2 = 10–100 books, 3 = Over 100 books). Approximately 22.7% of students reported 0–10 books, 53.1% reported 10–100 books, and 24.2% percent reported more than 100 books at home. Students were also asked, "How likely is it that you will be able to go to college?" (1 = Not at all likely, 1.5 = I don't know, 2 = A little Likely, 3 = Somewhat Likely, 4 = Very likely). The mean is 3.4 (S.D. = 0.83). We chose to use books in the home because youth are often unable to report accurately on parental income, and this is a widely used measure for youth assessing academic outcomes and achievement internationally (Provasnik et al. 2012). In addition, differences in career aspirations by social class have also been associated with different college expectations dependent upon social class (Grodsky and Riegle-Crumb 2012; Buchmann and DiPrete 2006; Legewie and DiPrete 2012).

We include race/ethnic minority status as a control variable. Students were asked, "What is your race/ethnicity? You can mark more than one answer." Response categories were; "Black/African American," "Latino/Hispanic," "Middle Eastern/Arabic" "White," "Asian," "Native American," "Pacific Islander," "Mixed," and "Other," with space to write in any other race/ethnic group. Approximately 30% of the respondents were white only. Latino (23.5%) and middle eastern (7%) are ethnic categories, so any student who marked these, no matter what other race category they marked, were included in the under-represented race/ethnicity minority category. About a fifth of the sample self-identified as black, 6% Asian, 6.2% Native American, and 3% other. We dichotomized the responses into minority = 1 (69.9%) or not minority = 0.

3. Results

3.1. Bivariate Results

We provide bivariate results by gender (shown in Table 1) to assess hypothesis 1, whether boys and girls differ on the desire to be a scientist, science possible selves, science confidence, and boy-science bias. For continuous variables, we used *t*-tests and for categorical variables we used chi-square tests. We find evidence to support hypothesis 1. Compared to girls, a higher proportion of boys want to be a scientist (10% vs. 5%, $p = 0.048$), and believed that they could become a scientist if they wanted to (26% vs. 19%, $p = 0.031$), and reported that they were 'Excellent' at science (24% vs. 16%, $p = 0.014$). More boys than girls believed that boys are better at science (had boy-science bias) (22% vs. 11%, $p = 0.003$). There were no significant differences between boys and girls on reported science grades, fixed mindsets, essentialist mindsets, or college expectations. There are no differences by gender for the control variables, minority status, and books in the home.

Table 2 shows the bivariate Pearson's r correlation matrix for the theoretical and control variables. The strongest associations in the matrix are between science grades and science confidence ($r = 0.40$, $p < 0.001$), science possible selves and the desire to be a scientist ($r = 0.37$, $p < 0.001$), and science confidence and science possible selves ($r = 0.35$, $p < 0.001$). Girls, minorities, and youth with less social capital have lower science possible selves and lower science confidence than boys, non-minorities, and those with higher social capital. Youth with lower grades and less social capital are also more likely to hold a boy-science bias. Grade level has a negative association with science grades, indicating that science grades are lower for youth in 8th compared to 6th grade.

Table 1. Bivariate Descriptive Statistics by Gender

	Boys (N = 284)		Girls (N = 245)		*sig.*
	Mean/Proportion	***S.D.***	**Mean/Proportion**	***S.D.***	
Desire to Be a Scientist	0.10		0.05		*
Science Possible Self	0.26		0.19		*
Science Confidence	0.24		0.16		*
Boy-Science Bias	0.22		0.11		**
Fixed Mindset	2.52	1.23	2.54	1.21	n.s.
Essentialist Mindset	2.71	1.31	2.61	1.27	n.s.
Science Grades	5.09	1.59	4.06	1.65	n.s.
Minority	0.69		0.70		n.s.
College Expectations	3.39	0.84	3.47	0.82	n.s.
Books in the home (0–10 reference)	0.24		0.25		n.s.
10–99 books	0.52		0.54		n.s.
100+ books	0.24		0.21		n.s.

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, n.s. = not significant.

Youth with fixed mindsets are less likely to have a science possible self ($r = -0.19$, $p = 0.001$), more likely to have boy-science bias ($r = 0.14$, $p < 0.021$), lower science grades ($r = -0.28$, $p = 0.001$), and lower college expectations ($r = -0.10$, $p = 0.018$). Also, youth with essentialist mindsets were more likely to have fixed mindsets ($r = 0.26$, $p < 0.001$), a higher likelihood of having a boy-science bias ($r = 0.10$, $p < 0.05$), had lower science grades ($r = -0.09$, $p = 0.041$), and lower college expectations ($r = -0.10$, $p = 0.18$) than youth without essentialist mindsets.

3.2. Multivariate Results

Table 3 shows the results of a series of logistic regressions with the likelihood of boy-science bias (Model 1 and 2) and science confidence (Model 3 and 4) as outcomes to test hypothesis 2, hypothesis 3a, and hypothesis 3b. Table 4 shows the results of a series of logistic regressions with the likelihood of a science possible self (Model 1 and 2), and the desire to be a scientist (Model 3) as outcomes to test hypothesis 4a, hypothesis 4b, and hypothesis 5.[1] All ordinal variables are mean centered to adjust for multi-collinearity, to more easily interpret the constant/intercept, and to solve for and plot significant interactions.

[1] We chose to dichotomize our dependent variables for multiple reasons. First, the explicit gender bias scale includes a girl science bias, but we dichotomized this variable and included those with a girl-science-bias with youth who report no bias because it is likely that a girl science bias has a different meaning and interpretation for boys and girls in a society with documented cultural biases favoring boys in science. We will explore girl-science-bias more fully in future work. Second, for the desire to be a scientist, science possible selves, and science confidence, we were interested in assessing the odds that someone would fall into the highest category compared to all others. We conducted a number of sensitivity analyses to assess how our results might differ if we use OLS regression on these four categories, and ordinal variables rather than the dichotomized variables. We found that the results varied little if we used the dichotomized or ordinal analyses. Our main findings for the associations of gender with the outcomes and among the core concepts (i.e., mindsets, gender bias, science confidence, science possible selves, and the desire to be a scientist) were similar for both approaches. Associations for two of the control variables (social capital and self-reported science grades) were significant in the OLS models with the ordinal outcomes but not in the logistic regression models with the dichotomous outcome. We interpret these differences in the models as indicating that social capital and science grades matter more when distinguishing among the lower categories.

Table 2. Bivariate Correlation Matrix.

	Desire to Be a Scientist	Science Possible Selves	Science Confidence	Boy-Science-Bias	Essentialist Mindsets	Fixed Mindsets	Science Grades	Minority	College Expectations	Books > 100	Grade Level
Science Possible Selves	0.37 ***										
Science Confidence	0.30 ***	0.35 ***									
Boy-Science-Bias	−0.01	−0.12 **	−0.03								
Essentialist Mindsets	0.06	−0.02	−0.06	0.10 *							
Fixed Mindsets	−0.05	−0.19 ***	−0.15 ***	0.14 **	0.26 ***						
Science Grades	0.14 **	0.22 ***	0.40 ***	−0.18 ***	−0.09 *	−0.28 **					
Minority	−0.03	−0.09 *	−0.11 *	0.06	−0.03	0.11 *	−0.12 **				
College Expectations	0.04	0.20 ***	0.13 **	−0.11 *	−0.10 *	−0.13 **	0.22 ***	−0.04			
Books > 100	0.05	0.11 *	0.15 ***	−0.10 *	0.02	−0.05	0.13 **	−0.20 **	0.13 **		
Grade Level	0.03	0.08 +	−0.02	0.04	0.01	−0.03	−0.24 ***	0.06	0.02	−0.02	
Girls	−0.08 +	−0.09 *	−0.10 **	−0.12 **	−0.04	−0.04	−0.04	0.01	0.04	−0.04	−0.04

Note: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3. Logistic Regression Models Predicting Boy-Science Bias [A] and Science Confidence [B].

	Boy-Science Bias						Science Confidence					
	Model 1			Model 2			Model 3			Model 4		
	β	SE	*p*	β	SE	*p*	β	SE	*p*	β	SE	*p*
Grade Level	0.08	0.15		−0.17	0.19		0.26	0.16	+	0.32	0.20	
Girl (Boy Reference)	−0.75	0.26	*	−0.81	0.27	*	−0.47	0.26	+	−0.48	0.26	+
GirlXGrade Level	-	-		0.72	0.33	*	-	-		−0.15	0.31	
Focal Independent Variables												
Mindsets												
Essentialist Mindsets	0.13	0.10		0.14	0.10		−0.05	0.11		−0.05	0.11	
Fixed Mindsets	0.24	0.10	*	0.24	0.11	*	−0.07	0.10		−0.07	0.10	
Boy-Science Bias							0.46	0.38		0.46	0.38	
Controls												
Science Grades	-	-		-	-		1.07	0.15	***	1.07	0.15	***
Racial/Ethnic Minority (White reference)	0.13	0.30		0.13	0.30		−0.18	0.26		−0.18	0.26	
Social Capital												
College Expectations	–0.15	0.14		−0.14	0.14		0.10	0.18		0.10	0.18	
Books in the home (0–10 reference)												
10–99 books	−0.56	0.29	*	−0.61	0.29	*	0.33	0.39		0.34	0.39	
100+ books	−1.09	0.39	**	−1.14	0.39	**	0.79	0.43	+	0.81	0.43	
intercept	−1.02	0.35	**	−1.16	0.68	**	−7.91	1.23	***	−2.24	0.46	***
Nagelkerke *R* squared		0.11	***		0.13	***		0.34	***		0.34	***

Notes: [A] Do you think boys or girls are better at science? Predicted = "Boys are a little/lot better at science." Reference = "Girls and boys are the same at Science," "Girls are a little/lot better at science." [B] How good are you at Science? Predicted = "Excellent." Reference = "Good," "Fair," "Poor." + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Logistic Regression Models Predicting Possible Selves [A] and Desire to be a Scientist [B].

	Science Possible Self						**Desire to be a Scientist**		
	Model 1			**Model 2**			**Model 3**		
	β	**SE**	***p***	**β**	**SE**	***p***	**β**	**SE**	***p***
Grade Level	0.33	0.15	*	0.33	0.15	*	0.28	0.25	
Girl (Boy Reference)	−0.40	0.24	+	−0.42	0.25	+	−0.27	0.40	
Focal Independent Variables									
Mindsets									
Essentialist Mindsets	0.12	0.09		0.11	0.09		0.25	0.15	
Fixed Mindsets	−0.28	0.11	*	−0.27	0.11	*	0.09	0.17	
Boy-Science Bias	−1.00	0.42	*	−1.04	0.47	*	0.26	0.57	
GirlXBoy-Science Bias	-	-		0.32	0.91		-	-	
Science Confidence	1.49	0.29	***	1.49	0.28	***	1.48	0.45	**
Science Possible Self	-	-		-	-		2.42	0.45	***
Controls									
Science Grades	0.13	0.09		0.11	0.09		0.09	0.16	
Racial/Ethnic Minority (white reference)	−0.15	0.25					−0.16	0.42	
Social Capital									
College Expectations	0.57	0.18	**	0.57	0.18	**	−0.21	0.25	
Books in the home (0–10 reference)									
10–99 books	−0.13	0.33		−0.13	0.33		−0.20	0.51	
100+ books	−0.04	0.38		−0.03	0.37		−0.26	0.58	
intercept	−1.27	0.38	**	−1.27	0.38	**	−4.88	1.38	***
Nagelkerke *R* squared		0.26	***		0.26	***		0.34	***

Notes: [A] Let's Pretend you wanted to become a scientist, could you become a scientist if you wanted to? Outcome = "I could become a scientist." Reference = "I might be able to become scientist," "I probably could not become a scientist," "I could not become a scientist," "I don't know." [B] How much do you want to become a scientist? Outcome = "A lot." Reference= "Some," "A little," "Not at all." + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.3. Boy-Science Bias and Science Confidence

Table 3, Model 1 shows the associations of grade level, gender, and fixed and essentialist mindsets with the likelihood of having a boy-science bias. The results show that girls are less likely to have a boy-science bias (β = −0.75, $p = 0.004$) after adjusting for other variables in the model. Additionally, we find evidence that partially supports hypothesis 2; fixed mindsets, but not essentialist mindsets, are associated with boy-science bias (β = 0.24, $p = 0.021$). Youth with fixed mindsets are more likely to have boy-science bias than youth without fixed mindsets.

In Model 2, to test for hypothesis 3a, we include a measure of the interaction of gender by grade level. There is support for hypothesis 3a because the interaction is significant on boy-science bias (β = 0.72, $p = 0.027$). The main effect for grade level is not significant, indicating that in the adjusted model, for boys, boy-science bias does not differ by grade level. Figure 1 shows the predicted probabilities for boy-science bias by gender and grade-level.

Figure 1 shows the predicted proportion with a boy-science bias for 6th, 7th, and 8th grade boys and girls. Among boys, there is a slight, non-significant decline in the proportion with a boy-science bias from 6th (31%) to 8th (24%) grade. The proportion of girls with a boy-science bias is largest for 8th grade girls (22%), smaller for 7th grade girls (14%), and smallest for 6th grade girls (9%). The difference between boys and girls is largest in 6th grade (22%).

Table 3, Model 3 shows the multivariate logistic regression model for science confidence. After adjusting for control variables, effects of gender and grade level are only marginally significant. There were trends that were marginal on science confidence for girls and by grade level. Girls have lower science confidence than boys (β = −0.47, $p = 0.067$). Higher grade level is associated with higher science confidence (β = 0.26, $p = 0.095$). Similar to the bivariate model, there is no significant relationship between boy-science bias, fixed mindsets, essentialist mindsets, and science confidence. The only significant association is between self-reported grades and science confidence (β = 1.07, $p < 0.001$). Although minority status and social capital had significant associations with science confidence in the bivariate model, they are no longer significant in the full multivariate model. In Model 4, we tested an interaction between gender and grade to assess hypothesis 3b; that boys' confidence would not vary by grade level, while girls' science confidence would be lower as grade level increase. We failed to find support for this hypothesis.

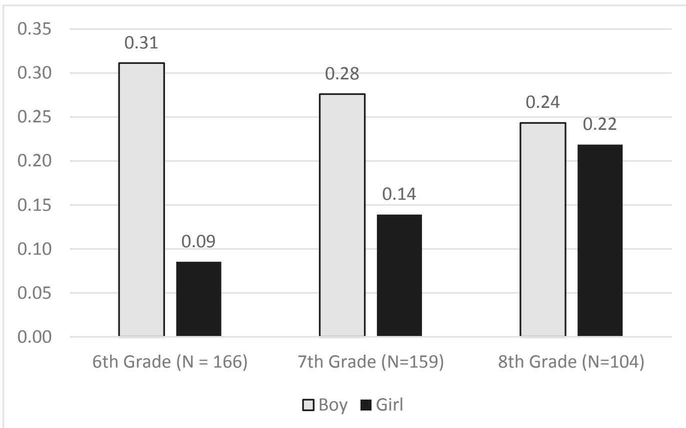

Figure 1. Predicted Proportion with a Boy-Science-Bias by Grade and Gender, adjusted for control variables.

3.4. Science Possible Self and the Desire to Be a Scientist

Table 4, Model 1 shows the multivariate logistic regression results for science possible selves. Results show that grade level has a positive association with science possible selves (β= 0.33, p = 0.025); therefore being in a higher grade is associated with higher science possible selves compared to being in a lower grade. Similar to the bivariate level, girls have lower science possible selves than boys ($\beta = -0.40$, p = 0.096), although the effect is only marginal after adjusting for controls. Science confidence has a significant association with science possible selves (β = 1.49, $p < 0.001$), followed by boy-science bias ($\beta = -1.00$, $p < 0.018$). Youth with fixed mindsets have lower science possible selves ($\beta = -0.28$, p = 0.013) than youth without fixed mindsets. In contrast, youth with college expectations have higher science possible selves (β = 0.57, p = 0.002) than youth without college expectations. In Model 2, we test an interaction of gender and boy-science bias to assess hypothesis 4a and hypothesis 4b. The results do not support hypotheses 4a and 4b; the association of boy-science bias with science possible selves does not differ for boys and girls.

Finally, we assess the relationship between all previous theoretical variables and the desire to be a scientist (Model 3). We find support for hypothesis 5; high science confidence is associated with higher odds of having a desire to be a scientist (β = 1.48, p = 0.001). Having a science possible self was also associated with higher odds of having a desire to be a scientist (β = 2.42, $p < 0.001$).

4. Discussion

This study provides a comprehensive analysis of how a fixed mindset and essentialist mindsets are associated with boy-science bias, science confidence, science possible selves, and the desire to be a scientist in a large sample of early adolescents in a U.S. middle school. Several findings are noteworthy. First, despite relatively high proportions of youth with high science confidence and high science possible selves (about 25%), very few say they want to be a scientist "A lot"; only approximately 7% in the whole sample. Although almost twice as many boys desire to be a scientist in the bivariate model (10% compared to 5%), gender differences are not significant in the adjusted model, indicating that gender gaps in science are related to differences in science possible selves and science confidence among boys and girls. Indeed, science confidence and a science possible self were both independent predictors of a strong desire to be a scientist.

While the only significant association with science confidence was self-reported grades in science in the multivariate models, science possible self was associated with many more variables. Girls, youth with a boy-science bias, and with a more fixed mindset were less likely to have a science possible self, while grade level, science confidence, and college expectations were associated with a higher likelihood of a science possible self. Although we do not find that a boy-science bias has a direct association with youth desire to be a scientist, it has a negative association with a science possible self for boys and girls. Therefore, higher levels of boy-science bias in 8th grade girls compared to 6th grade girls may explain at least some of the emergent gender gap in science during early adolescence.

Although we hypothesized that a boy-science bias would be associated with lower odds of having a science possible self for girls, and possibly higher for boys, we found it was associated with having a lower likelihood of a science possible self for boys and girls. Theories about in-group biases led us to hypothesize that a boy-science bias might give boys' science possible self a boost or lift (Walton and Cohen 2003). We therefore plan to conduct more research to understand how boy-science bias could operate in the same way for boys and girls. It may be that some boys have unrealistically high expectations of themselves, which do not match their perceived ability. It might also be the case that strong in-group favoritism may be protective against low self-appraisal/self-esteem related to underachievement or disinterest in science.

Science confidence had robust associations with having a science possible self and desire to be a scientist, and the trend was that girls, on average, had lower confidence. The associations, however, were only marginal in the multivariate model. We also did not find evidence that confidence differs by grade between boys and girls in adolescence, although youth in higher grade levels had more confidence than in lower grades, exploratory analyses suggest this is driven by boys' confidence increasing relative to girls, and not girls' confidence decreasing. Science confidence has significant associations with having a science possible self and the desire to be a scientist. Efforts to increase science confidence among youth and longitudinal follow-up could better identify if such efforts could help boys and girls maintain science interest and career aspirations.

Fixed mindsets about intelligence were associated both with a boy-science bias, and with science possible selves in multivariate models. Essentialist mindsets were only associated with boy-science bias and fixed mindsets in the bivariate models, and were not associated in the multivariate models. These intriguing findings indicate that youths' beliefs about intelligence, whether it is fixed or malleable, are associated with boy-science bias and science possible selves. Therefore interventions to foster growth mindsets and science possible selves could maintain, widen, and broaden interest and persistence in STEM (Leslie et al. 2015; Meyer et al. 2015).

As with all research, there are important limitations to the generalizability of these results. First, this is a study of a single school; schools can vary considerably, and variables associated with adolescent culture might influence gender identity and gender stereotypes (Legewie and DiPrete 2014). Second, this study is cross sectional. Although we interpret the differences between sixth, seventh, and eighth graders, it is possible that the differences we see are cohort effects and not developmental effects. Although theory and empirical research supports that there is likely a developmental change in boy-science bias views, we cannot conclude from these findings that the differences we see by grade level are necessarily developmental. We would need a longitudinal study to assess how these attitudes change over time.

Our measures of social capital are limited, and recent research linking social capital with "science capital" and science career aspirations indicates that this is likely an important aspect of science career aspirations and science identity for adolescence (Archer et al. 2015). Future studies should consider including measures of socioeconomic status, and in particular, "science capital" including exposure to scientists, and exposure to science media, and informal science outside of schools (Archer and DeWitt 2015). The association between mindset, stereotyping, and science possible self is another possible rich avenue for exploration. Although much of our emphasis is on reducing the relevance of gender for STEM engagement, it might be worth exploring if in-group bias favoring science is protective against gender stereotypes. A longitudinal study of youth from 4th through 8th grade to assess change in mindsets, boy-science bias views, and science possible selves might unpack how these constructs change over time for girls, and lead to possible promising areas for interventions.

Overall there is evidence that decreasing fixed and increasing flexible mindsets has the potential to increase science possible selves and the desire for a job in science. Efforts to help youth learn about how they learn and the possibilities for learning (i.e., that they do not have to be born a scientist), seem promising for increasing interest in science careers. Attempts to de-gender science or to make science gender neutral may also be worthwhile because boy-science bias was associated with lower science possible selves for boys and girls. Finally, providing more concrete information about possible science careers could help youth to imagine a possible self with work involving science.

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Planning a Career in Engineering: Parental Effects on Sons and Daughters

Jerry A. Jacobs [1,*], Seher Ahmad [2] and Linda J. Sax [3]

1 Department of Sociology, University of Pennsylvania, 3718 Locust Walk, McNeil Building, Rm. 113, Philadelphia, PA 19104-6299, USA
2 Harvard Strategic Data Partnership Fellow, Delaware Department of Education, The Townsend Building, 401 Federal Street, Suite 2, Dover, DE 19901-3639, USA; seher.ahmad@doe.k12.de.us
3 Graduate School of Education and Information Studies, University of California, Los Angeles, CA 90095-1521, USA; lsax@ucla.edu
* Correspondence: jjacobs@upenn.edu; Tel.: +1-215-898-1536

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Abstract: This paper examines the extent to which prospective engineers follow in their parents' footsteps. Specifically, we investigate the connection between fathers' and mothers' employment in the engineering profession and the career plans of sons and daughters. We develop a number of reasons to expect an occupation-specific intergenerational association in this field, as well as hypotheses regarding gender-specific role-modeling. Data are drawn from the UCLA HERI Freshman Survey data spanning 1971 to 2011. The results point to clear and substantial effects on sons and daughters' plans to pursue engineering, connections that cannot be explained by typical pathways such as social background, education and values. The evidence points to a pattern of increasing salience of mothers with respect to the career plans of their children, especially their daughters. The implications of these findings for the under-representation of women in engineering and for gender-specific family dynamics are discussed in the conclusion.

Keywords: gender; STEM fields; career choices; college majors; occupational mobility

1. Introduction

Despite a long and rich history of research on occupational mobility and career choice, researchers have rarely explored intergenerational occupational inheritance at the level of specific occupations. In this paper, we add to a small and diverse literature on this topic by investigating the extent to which college freshmen plan to follow their parents into the engineering profession.

The under-representation of women in STEM (Science, Technology, Engineering and Mathematics) fields has long been the focus of considerable scholarly attention [1–5] and public policy initiatives [6–9]. In particular, policy makers are concerned about a shortage of individuals trained for engineering and other STEM professions. Indeed, interest in generating a skilled labor force underlies much of the research on STEM fields [10,11].

The economic impact of the two and a half million engineers currently employed in the US far surpasses their numbers. Working in diverse industries, they plan roads, bridges and weapons systems for the government, design new products for consumers, monitor and improve production processes in manufacturing and energy production, and develop materials for use in construction, medicine, and many other fields [12,13].

Sociologists have long been interested in engineering [14] due to its status as a profession often based in large corporations [15] and for its role as an exemplar of the knowledge society [16]. In more recent years, the gender and racial homogeneity of practitioners has taken center stage among sociologists interested in engineering [17,18]. Indeed, engineering is the largest of the STEM majors and is the career most often mentioned by male freshmen [19]. The under-representation of women and minorities is particularly notable in the case of engineering [20].

Examining occupational choices among parents and children will help us to understand the under-representation of women in this field. Research on the determinants of women's entry into the field of engineering has paid relatively little attention to parent's employment in engineering [21]. Sikora and Pokropek (2012) represents a notable exception. If sons are more likely than daughters to follow their fathers into engineering, this differential would contribute to women's under-representation in engineering. Similarly, if daughters are more likely to pattern themselves on their mothers, and if mothers are substantially under-represented in engineering, then this gender-specific role-modeling pattern could contribute to young women's continuing under-representation in this important field. These are among the possibilities we investigate [21].

In addition to contributing to our understanding of diversity in the field of engineering, this study promises to contribute to our understanding of gender patterns within families. By examining gender-specific role models, and investigating whether the salience of mothers' careers has increased over time as women's careers have become more established, we hope to shed light on the way gender inequality is reproduced and how these patterns may be evolving over time. The large and unique data set we tap provides unparalleled opportunity to assess change over time and to make detailed distinctions, such as differentiating between families in which both parents are employed as engineers and those in which only the mother is an engineer.

Understanding freshman plans to pursue a career in engineering should be understood as representing one point in the career-development process. Engineering, along with other STEM fields, experiences considerable attrition during the undergraduate years, and significant gender differences in persistence continue to be evident [22–25].

This line of research often focuses on the scientific "pipeline," that is, stages in the educational career where women may "leak out" of pathways towards a career in engineering [26–28]. For the purposes of understanding the career plans of college freshmen, engineering is a useful case in part because there is a clear link between the choice of field of study in college and the pursuit of a career. Specifically, freshmen who express an interest in pursuing a career in engineering also are likely to plan to major in engineering [29]. In many cases, there is an additional behavioral step involved. In other words, engineering is often located in its own collegiate division or school and frequently requires a separate application process. In short, the plan to pursue a career in engineering represents more than checking off one box in a list of possible careers. We will examine the issue of the predictive validity of freshman career intentions in more detail below.

Finally, given its reliance on data spanning several decades, this study will help us understand change over time. We are particularly interested in exploring whether the salience of mothers in their children's career choices has grown over time.

2. Scarcity of Studies of Occupational Inheritance

Researchers from several distinct disciplines have approached the question of occupational assortment using a variety of theoretical frameworks. As we will see, researchers have often focused on self-selection into occupational types or clusters rather than individual occupations. This pattern is evident in both social-psychological studies [30,31] as well as research on social mobility conducted by sociologists [32].

This psychological literature, for example, emphasizes the role of personality and values in the choice of occupations as well as the persistence in these careers. Another approach to intergenerational inheritance employs occupational indices such as prestige scales or socio-economic status scores [33].

Similarly, economic studies have generally emphasized intergenerational connections with respect to income rather than via specific occupations per se [34,35].[1]

There is a widely dispersed literature on the recruitment and retention of employees in particular occupations [36–38]. These fields often come to be studied because of perceived shortages, high turnover, or the belief that the unique demands of a particular field require a very specific personality type. These occupation-specific studies typically do not focus on the inter-generational association. The main exceptions have been volunteers for military service [39] and self-employment. A variety of studies have found that children whose parents were self-employed are much more likely to be self-employed themselves [40,41].[2]

The scarcity of research on intergenerational connections to particular occupations may well be due in part to the large amount of data needed to pursue this issue, since individual occupations often represent one percent or less of a sample. Fortunately, the UCLA Higher Education Research Institute (HERI) freshman surveys are large enough to allow for the analysis of small but important subgroups.

The questions investigated in this study most closely match those examined in an exemplary paper by Sikora and Pokropek (2012) [21]. They considered the impact of parents' careers on children's plans to pursue STEM careers using data on fifteen-year-old students from 24 countries. The differences between our study and theirs include the following: (a) their study does not focus on engineering alone but groups this field with computer science and mathematics; (b) we are able to examine changes over time in the relationships between parents (especially mothers) and children; (c) our results pertain to college freshmen, who are several years older than the students included in Sikora and Pokropek's study. Not only are college freshmen older and more focused on their career plans, but we are observing them at a particularly critical time in the selection of their field of study.

3. Theorizing Intergenerational Connections

It should be noted that there is a broad cultural emphasis on the importance of young adults making their own choices. In other words, parents (at least in the US) are broadly enjoined from issuing specific career directives for their children. Instead, parents' role is often seen as "guiding, not deciding" for their children [42].[3] Advice columnists and parenting guides urge parents to help their children pursue opportunities for self-discovery and appropriate information rather than direct them toward a goal of the parents' choosing [43]. In fact, as we will see, the vast majority of children pursue careers that differ from those of their parents.

There are nevertheless a number of reasons to believe that children will be disproportionately likely to follow in their parents' footsteps. There are at least three sources of a connection between the careers of parents and their children: familiarity, values and skills. The world of work is comprised of a bewildering array of specialties, and consequently there are many fields of work which may not be familiar to the average 18-year-old. In general, children are exposed to their parents' career choices, although they may not be acquainted with the details of the job. If occupational choices are disproportionately concentrated among familiar fields, and if children are at least acquainted with their parents' jobs, then children will disproportionately express an interest in the same career choices as their parents. In Sorensen's (2004) memorable formulation, exposure (to parent's occupational experiences) leads to social closure, that is, a tendency for in-group members to have advantaged access to a social position over out-group members [41].

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1 Several economic studies of intergenerational inheritance in specific occupations are discussed below.

2 Self-employment across generations is a complex matter, as not all children take over their parents' business. Moreover, many self-employed individuals are supplementing other family income by working part-time.

3 Parents of students at the University of Minnesota divided roughly between those who felt parents should have "some" influence over their children's career choices (45%) and those who felt that parents should have "a little" or "very little" influence (49%) (University of Minnesota, 2011). Very few parents maintained that they should have "a lot" of influence (less than 2%, and only a small fraction felt that parents should have no influence (less than 4%).

Children may also absorb occupationally-related values from their parents. For example, some parents may emphasize the importance of service as a necessary component of meaningful work, while others may stress the importance of job security or pecuniary success. Many studies have documented the inter-generational congruence of connection of values, although the connections are sometimes weaker than one might expect and the pathways can be hard to pinpoint [44–47].

A final reason for expecting children to follow in their parent's footsteps relates to the acquisition of skills. Children may absorb some of the 'tricks of the trade' by watching their parents work and listening to their parents' stories. This mode of human capital acquisition has been emphasized for self-employment and family farms, where children are likely to have direct exposure and even involvement, a form of on-the-job training. Some researchers find that those who have inherited occupations from their parents earn more than those whose parents were employed in different fields ([48]; but see Sorensen (2004) for an exception [41]). They attribute this earnings advantage to the assimilation of occupation-specific skills during childhood and adolescence by those who follow in their parents' footsteps.

To summarize, despite a general cultural emphasis on the importance of individual choice, we expect that children are likely to disproportionately select their parents' current career as their own occupational goal.

4. Engineers' Job Satisfaction

The tendency of children to follow their parents' career choices assumes that the parents themselves have a generally positive view of their career choices. While it is difficult to summarize feelings about the engineering profession, since it represents such a large and diverse set of careers and employment settings, there are nonetheless several reasons to believe that parents convey a generally positive assessment of their careers in the field.

Professionals tend to view their careers in a favorable light, and engineers are no exception in this regard [49]. Our analysis of job satisfaction using data from the General Social Survey (GSS) reveals that engineers are not statistically distinguishable from other professionals in their level of job satisfaction.[4]

When the Gallup organization asked respondents what kind of work or career they would recommend to a young man or woman, engineering ranked in the top 7 for both genders, and combining "engineering" with "technology/electronics" and "computers" would place this cluster of fields second only to medicine [50]. One survey reports that engineers generally regard their work as "interesting and rewarding" (77%), and that 84% would recommend and engineering career to their child or to a friend's child [51].

An additional consideration that should be noted here is that parents of college freshmen are generally older, and job satisfaction increases with age. This is due in part to the fact that job rewards increase with age [52]. It is also the case that parents who are engineers when their children are in college represent those who have survived or persisted in the field of engineering. Many of those who were disgruntled or unsatisfied with engineering would have left the field by this stage in their lives [53]. Since parents of college freshmen are generally in their forties or fifties, they may well offer a more positive evaluation of the field than those who were dissatisfied and left to pursue other lines of work.

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[4] The main caveat here is the small sample size, due to the fact that job satisfaction is not included in every administration of the GSS, and the fact that only a small fraction of working Americans report that they are employed as engineers. We conducted the comparison for the 53 engineers in the GSS sample as well as for a broader set of architects, engineers and scientists (n = 96).

5. Fathers and Mothers, Sons and Daughters

Thus far, we have reviewed reasons for parental effects without differentiating between fathers and mothers on the sending side and sons and daughters on the receiving side. Now, we turn to the issue of gender-specific connections. The father-son relationship has been the focus of the greatest attention. In our view, this reflects the historical assumption that the status of the family depends on the father's occupation and earnings. In other words, if the male is assumed to have the breadwinner role [54], the connection between fathers and sons is the key association in terms of intergenerational transmission of status.

Research on intergenerational social mobility has most commonly taken father's occupation as a measure of 'social origins,' whether or not daughters are included along with sons in the research [55], despite substantial evidence that mothers also influence children's outcomes. When mothers are added to the model, their influence has usually been conceptualized as rooted in their education rather than their occupation (see [56] for a review, and [57] for an exception). However, women's employment has grown to the point that the majority of mothers work for pay, including mothers of pre-school children [58]. The vast majority of undergraduates are able to list a career for their mothers, and only a minority list their mother's occupation as "homemaker."[5] In this context, it is important to develop specific hypotheses regarding the effects of both fathers and mothers on the career choices of sons and daughters.

We expect the occupation-specific father-son connection to be stronger than the father-daughter connection. Daughters who choose to follow their fathers must overcome gendered stereotypes about careers in engineering and science (see [17,25] cited above). In other words, we expect that it will be easier for sons to follow their fathers because there are a host of social and cultural obstacles in the way of daughters who may be inclined to do the same.

The voluminous literature on role models suggests a mother-daughter connection. Researchers have long suggested a connection between positive maternal role models and daughters' engagement in paid employment [59].[6] Now that mothers' employment is common, we expect that mothers will not only represent a model of employment but of specific occupational choices as well. More recent research, in both experimental and natural settings, has provided evidence that non-familiar female role models, serve to counter gender-stereotypes [61]. A central question, then, is whether the presence of a significant role model within the family in a gender-atypical setting effectively counters the broader cultural barriers to the daughter's pursuit of a male-dominated field, in this case a career in engineering.

Sikora and Popropek [21] lay out the role-modeling thesis in detail with respect to careers in sciences. They find that role models are influential in the choice of scientific careers, and parents in particular serve as powerful role model.

Marks [62] carefully maps out several specific gender-specific role-modeling effects. Specifically, he investigates whether fathers have stronger effects on boys in terms of the influence of the fathers' socio-economic level, occupational status and educational attainment. The mother-daughter association for these same three factors are also posited to be stronger than the gender-discordant relationships. Drawing on data covering over 170,000 15-year-old students in 32 countries, Marks finds some evidence of these gender-specific relationships on children's student performance, but these associations are not consistently evident within countries or across countries. Marks concludes that it makes relatively little difference which parent contributes resources to the family as long as the mother works for pay. He also finds no evidence of change over time in the impact of mothers relative to fathers.

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5 In the 2015 HERI survey, 15.0% of freshmen listed their mother's occupation as "homemaker/stay at home parent" while 2.0% of fathers were classified this way. See Eagan et al. [19].

6 See Gerson [60] for a useful corrective to an overly simplistic view of stay-at-home or working mothers as role models.

Rather than abandon the premise of gender-specific role models, this study will pursue these questions in terms of a substantively different parent-child connection. We posit that that the parent-child connection may well be stronger in terms of the child copying the parent's specific occupational field rather than in terms of students' overall educational performance. The general socio-economic relationships that Marks investigates are rather diffuse and children may not differentiate between their father's and their mother's attributes in this particular way. In other words, if children experience their family's overall social standing as a whole, it may not always be possible to tease out separate effects of mothers and fathers, especially as parents are increasingly matched on their educational levels [63]. In contrast, the particular occupational and career experiences of parents may well be more salient and not reducible to a general socio-economic dimension. Thus, there is reason to believe that, when it comes to career choice, sons may be more likely to copy their fathers while daughters copy their mothers.

In addition to redirecting the question to occupational specific connections, we reframe the question in terms of change over time. Mothers' impact on the career goals of their children may be more salient today than was the case a generation or two ago, when fewer mothers worked outside the home for pay, and when commitment to a full-time career was less common than it has become.

As women spend a greater portion of their lives in the labor force, it may be that their occupational choices are becoming increasingly influential in their children's development of career aspirations. Consequently, we expect that the salience of mothers' careers may well have increased over time, especially in terms of their connection with the career choices of their daughters. We expect that mothers will have disproportionate effect on their daughters rather than their sons, and that the effect on both sons and daughters will have grown in recent decades.

It should also be noted that mothers who remain employed as engineers by the time that their daughters are entering college are a selected group. There is evidence of attrition from engineering at all stages, from the point of college entry and continuing throughout the career, and exit rates are higher for women than for men (see [23–25,53]). Consequently, the role-modelling of mothers in this case needs to be understood against this backdrop. In other words, the mothers who survived in engineering are more likely to be committed to this career, and their daughters are likely to be cognizant of this fact.

In this regard, our hypothesis is quite different than that developed by Hellerstein and Morrill [64], who find evidence of an increasing association over time between the career choices of daughters and their fathers. They posit that this reflects a greater level of "occupational-specific" human capital investments on the part of fathers in the context of a greater likelihood that their daughters are going to spend a significant portion of their careers in the labor market. It is possible, then, that the Hellerstein-Morrill effect may off-set a potential increase in the mother-daughter connection. Of course, it is possible as well that there has been an increase in both the father-daughter and mother-daughter connections. We revisit the Hellerstein-Morrill issue with data that spans the period during which mothers' labor force attachment was increasing.

6. Parental Occupational Homogamy

One important consideration in assessing the potential impact of mothers who are engineers is the fact that a very large fraction—almost half—of students whose mothers are engineers also report that their fathers are engineers. Consequently, a simple assessment of the mother's impact on her children will overstate her influence because in many cases this will actually represent the combined effect of fathers and mothers. Because we have such a large sample, we are able to separate engineering families into those which are father only, mother only, or both parents.

7. Research Questions

The specific goals of this study include efforts to answer a series of inter-related research questions:

Research Question 1: Is there an increased likelihood of planning a career in engineering if one or more of the respondent's parents is an engineer?

Research Question 2: Does the association between parents' and children's careers vary for fathers and mothers, and sons and daughters, as well as the case in which both parents are engineers?

Research Question 3: Have these associations increased or declined over the last four decades?

Research Question 4: Are parental effects mostly mediated by particular pathways, such as values and preparation, or is most of the parent–child association a largely unexplained residual?

8. Data and Methods

Our research taps into data collected by the Cooperative Institutional Research Program (CIRP), a nationwide study of college students housed at the Higher Education Research Institute at the University of California, Los Angeles. The HERI Freshman Survey, a national longitudinal study of college students in the United States, annually obtains responses from entering college students regarding their demographic backgrounds, high school experiences, affective traits such as self-concepts and values, and goals and aspirations related to college and beyond.

Data for this study cover the period 1976 through 2011. The analysis reported here is based on a sample of nearly 1 million first-year students. This sample is stratified by institutional type, control and selectivity. Weights are applied in order to make the results representative of freshmen enrolled full time at four-year institutions in the United States [19].

Entering freshmen are asked to indicate their intended career as well as the careers of their parents based on a list of several dozen career goals on the survey. This occupational list forms the basis for the dependent variable in this study as well as the two key independent variables. Students who designated "engineer" as their career goal were assigned a value of 1; other occupational plans were assigned a value of 0. The same procedure was applied to students' reports of the parents' occupations. The odds ratios for father-son, father-daughter, mother-son and mother-daughter associations are calculated. These and other analyses are reported separately by gender. The trends in these associations are also reported.

Once the associations between first-year students' plans to enter engineering and their parent's employment in engineering were established, we sought to identify whether these associations were mediated by identifiable measures. In other words, we examined whether the parent-child association could be explained by factors such as academic self-concept or student values, or whether the association was a direct one, net of mediating factors. We employ logistic regression analysis, given the 0/1 nature of the dependent variable. We also checked on the robustness of the model by re-estimating it with OLS (ordinary least squares) regression as recommended by Mood [65].

The control variables employed in this study were prepared as part of a larger project on the determinants of majoring in STEM fields. The selection and grouping of other independent variables draws on Lent, Brown, and Hackett's [66] Model of Career Related Choice Behavior (MCRCB). Variables were divided into four groups:

- Race, Ethnicity and Religion
- Socio-economic Characteristics
- Educational Preparation, Self-Rated Abilities and Aspirations
- Personality, Interests and Goals.

  - *Race, Ethnicity and Religion:* Race dummy variables (vs. White) include African-American, Asian-American, Latino/Chicano and Native American. Religion (versus Protestant) dummy variables include Catholic, Jewish, Other and None.
  - *Socio-economic Characteristics:* Family Income, Mother's and Father's Education, Race, Ethnicity and Religion, and Financial Concern for College,

- *Academic Preparation, Self-Rated Abilities and Aspirations:* High School GPA, Self-rated Mathematics Ability, Scholar Personality (factor), Degree Aspiration, Expectation of Making at Least a B Average, Expectations of Changing Major Field, Educational Reasons for Going to College (factor).
- *Personality, Interests and Goals:* Leader Personality (factor), Scholar Personality (factor), Goal of Making a Theoretical Contribution to Science; Goal: Developing a Meaningful Philosophy of Life; Goal: Raise a Family; Social Activist Personality (factor), Artistic Personality (factor), and Status Striver Personality (factor), Educational Reasons for Going to College (factor), Extrinsic Reasons for Going to College (factor).

The principal focus is the effect of these blocks of variables on the strength of the parent–child connection. The goal of the analysis is to determine whether these groups of variables account for, or explain, the impact of parents on their child's choice of engineering as a career goal. The construction of the factors and other specifics regarding these control variables can be found in the appendix section of this paper.

While we draw on a very large data set spanning a long period of time with an extensive set of variables, there are limitations to this study, as is inevitable in any research of this kind. The data we examine do not follow students over their undergraduate years and into their careers. Thus, while we are able to shed light on a key moment in the career development process, we are unable to address questions regarding persistence into engineering and other STEM careers. The UCLA HERI Freshman Survey data also do not include questions regarding how involved parents are in their children's career choices, questions that are available in some other studies, e.g., [67]. We also do not have direct measures on parents' values. We are thus in a position of inferring value transmission from student reports rather than comparing students' and parents' reports.

9. Results

Figure 1 displays trends in the percent of freshmen indicating that they plan to major in engineering. For most of the last forty years, these figures have hovered between 12% and 18% for men and 2% and 4% for women. The fraction of women indicating an interest in engineering has increased since the 1970s, when it was 12%–13% as high as men's;[7] it has ranged from 18% and 22% of men's level of interest since then.[8]

Are sons of engineers more likely to follow their fathers into engineering, and daughters more likely to follow their mothers? Pertinent data are presented in Table 1. Summarizing over the entire period 1976–2011, the findings indicate that a significant minority of sons of engineers (27.4%) plan to follow their fathers into this career field, compared with 13.3% of their male classmates.

A brief discussion of probabilities, odds and odds ratios may be helpful in understanding these patterns. The *probability* of a young man aspiring to engineering if his father is an engineer is 27.4. The *odds* of his aspiring to engineering if his father is an engineer is 27.4/72.6 = 0.377 ($p/1 - p$). For young men whose fathers are NOT engineers, the corresponding odds are 13.3/86.7 = 0.153. The odds ratio for young men with and without engineering fathers is therefore 0.377/0.153 = 2.46, meaning that those with an engineering father are 146% more likely to aspire to an engineering career than those without an engineering father.

While daughters are much less likely to plan to become engineers than are sons, there is nonetheless an increased likelihood associated with parental employment in this field. Daughters

7 For example, in 1976, 1.93% of women and 14.99% of men planned a career in engineering; thus, women's level of interest was 13.4% (1.93/14.99 = 13.4%) as high as men's.

8 Figure 1 indicates an increase in interest in engineering careers on the part of both freshman men and women that coincided with the start of the Great Recession. This increase is also reflected in a growth in the number of engineering majors and enrollment in schools of engineering [68].

whose fathers or mothers are engineers are more likely to enter engineering (6.3% and 11.9%, respectively), than are those whose parents are engaged in other occupations and professions (2.3%–2.6%).

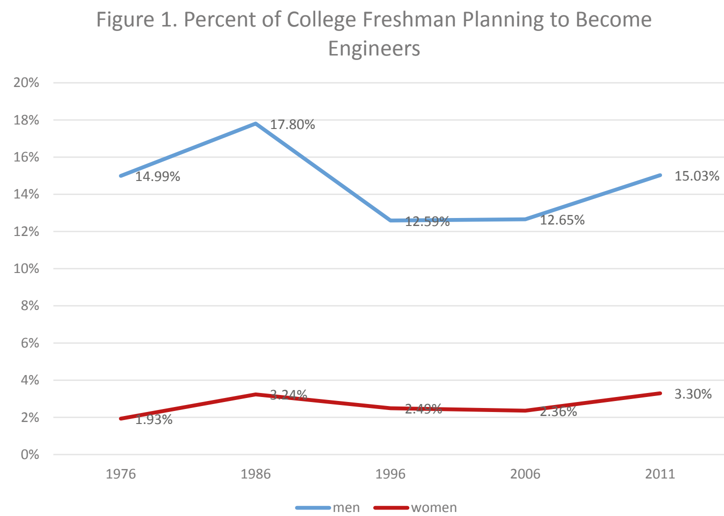

Figure 1. Percent of College Freshman Planning to Become Engineers.

For all four parent-child relationships, there is a considerable effect of parents' careers on their children's choices. Expressed in terms of an odds-ratio, the odds of entering engineering more than double (2.45) if the father is an engineer.

A strong father-daughter connection appears when this association is depicted in terms of an odds ratio (2.85). This does not mean that daughters of engineering fathers are more likely to become engineers than male counterparts. Rather, it indicates that the relative effect of fathers (starting at a very low baseline) is as large if not larger for daughters than for sons. The mother-daughter connection appears to be the strongest of all of the parent-child dyads (odds ratio = 5.06), but further analysis is needed to refine this conclusion. The gender-specific associations conform to our expectations in some respects but not in others. The main surprise is the disproportionately large effect of mothers on both their sons and daughters. As we will see shortly, this effect is not quite what it seems, as it is in part a "both-parents" effect.

The unstated pattern in the first panel of Table 1 is the fact that many mothers who are engineers have spouses (or at least co-parents) who are also engineers. While of course not all parents are married or remained married by the time their children enter college, understanding the impact of parental occupational homogamy is necessary for fully addressing the issue of gender-specific role-modeling. Overall, 8.5% of all freshmen have only a father who is an engineer, 0.5% only have a mother who is an engineer and 0.24% report that both parents are engineers. There is an interesting asymmetry in mothers' and fathers' engineering careers. Nearly half of students who report that their mothers are engineers also report that their fathers are engineers (47.2%), while only a small fraction (2.8%) of students with engineering fathers report having a mother who is an engineer.[9] This reflects the fact that women engineers represent such a small minority in this profession. This asymmetry will reappear in interpreting other findings as well. This pattern of occupational homogamy among parents

[9] This pattern holds for a number of occupations, including physicians [69].

requires us to separate out parents into four categories: the (a) father is an engineer while the mother is not; (b) the mother is an engineer while the father is not; (c) both parents are engineers; and (d) neither parent is an engineer.

Table 1. Interest in Engineering by Parental Engineering Employment and Gender.

A. Sons			
percent indicating engineering as a career plan			
father engineer	father not engineer	mother engineer	mother not engineer
0.274	0.133	0.305	0.145
B. Daughters			
percent indicating engineering as a career plan			
father engineer	father not engineer	mother engineer	mother not engineer
0.063	0.023	0.119	0.026
C. Sons, Differentiating Father only, Mother only and Both Parents as Engineers			
percent indicating engineering as a career plan			
father only engineer	mother only engineer	both parents engineers	neither parent engineer
0.270	0.236	0.382	0.133
D. Daughters, Differentiating Father only, Mother only and Both Parents as Engineers			
percent indicating engineering as a career plan			
father only engineer	mother only engineer	both parents engineers	neither parent engineer
0.060	0.077	0.165	0.023

The effect of fathers on their sons and daughters declines slightly when the association focuses on families in which only the father is the engineer. (The odds ratio declines from 2.45 to 2.38 for sons.) This slight change is due to the fact that a small number of "both parent" engineering families are included in the results reported in Panel A of Table 1. When this group is removed, the father-son relationship declines marginally. There is much more sizable decline in the mother-son association when dual-engineering families are removed due to the concentration of engineering mothers in this group. The mother–son odds ratio declines from 2.60 to 1.81 when the analysis focuses on mothers only.

The same pattern holds for daughters. There is still a considerable father-daughter connection in Panel D of Table 1 (odds ratio is 2.65), but the effect of mothers on daughters is considerably attenuated (odds ratio = 3.08, compared with 5.06 when dual-engineering parents are included).

When both parents are engineers, the parental effect more than doubles for sons and nearly doubles for daughters. A large minority (38.2%) of sons plan to pursue engineering when both of the parents are engineers, while for daughters the rate is about one in six (16.5%). This rate is roughly the same as what would be obtained by adding the impact of both fathers and mothers. This finding speaks to the power of families to affect the career choices of their children.

The results presented in Table 2 speak to trends over time in parent-child associations. Rather than portraying these connections as reflecting some enduring psycho-social dynamic within families, our analysis opens up the possibility that these relationships vary over time.

Table 2. Time Trends for Parent Child Association.

A. Sons	Odds Ratios				
	Father	**Mother**	**Father only**	**Mother only**	**Both Parents**
1976	2.43	2.15	2.41	1.24	4.58
1986	2.29	1.70	2.27	1.28	2.85
1996	2.35	1.98	2.31	1.47	3.01
2006	2.50	2.72	2.42	2.03	3.57
2011	2.71	3.41	2.52	2.32	4.39
All Years	2.45	2.60	2.38	1.81	3.63
B. Daughters	**Odds Ratios**				
	Father	**Mother**	**Father only**	**Mother only**	**Both Parents**
1976	3.22	2.21	3.19	-	-
1986	2.51	2.25	2.47	1.69	5.85
1996	2.53	4.14	2.42	3.09	5.75
2006	3.11	5.38	2.77	3.02	7.90
2011	3.01	5.18	2.60	3.34	6.75
All Years	2.85	5.06	2.65	3.08	7.35

Note: Missing values for 1976 reflect low samples sizes. The 1986 results for mother only and both parents represent an average of 1976 and 1986 data.

In Table 2, we see a steady increase over time in the effect of mothers who are engineers on the career choices of their children. These results are presented graphically in Figure 2a,b. Focusing on the father-only and mother-only trends, for sons, mothers' impact is much weaker than that of fathers at the start of the study period. The gap, however, narrows considerably, and since 2006, the connection between mothers' careers and their sons' career choices is considerable (odds ratios in excess of 2.0 for 2006 and 2011). For daughters, however, the marked increases in mothers' effect now reveal a stronger mother-daughter connection than is the case between fathers and daughters. The mother-daughter association jumped in the 1990s and has remained strong (odds ratios above 3.0) ever since.[10]

The results presented in Table 2 underscore the importance of examining change over time. Specifically, the relative influence of parents on daughters shifts over time. Fathers had more impact than mothers on their daughter's career choices in the 1970s and 1980s, and this pattern shifts to a gender-specific role-modeling pattern since the 1990s.

In the multivariate analyses, we estimated the effect of several sets of variables in addition to parents' occupation on the choice of engineering. In other words, we added groups of variables in order to see how much they reduced the intergenerational associations presented in Tables 1 and 2. Coefficients for parental engineering status from nested (or step-wise) regression results are presented in summary form in Tables 3 and 4. The full models are presented in Tables A3 and A4.

Intergenerational effects remain strongest for same-gender parents, and the overwhelming majority of the parent-child association is a direct effect, independent of the mediating variables included in our model. In other words, other indicators of social background, children's academic preparation and values, self-efficacy, etc., are responsible for only a small portion of the parent-child association observed. This pattern is particularly clear for fathers and sons, where nearly 90% of the association remains after controls are added to the model. The pattern also holds almost as well for fathers and daughters.

The influence of mediating variables is stronger in understanding the effect of mothers: roughly one quarter of the father-daughter association is mediated by the control variables, as is nearly

10 The cell sizes for 1976 were too small to report when we tried to differentiate between mother-only and dual-career marriages, but the increasing maternal effect is evident in the overall mother's effect reported in Table 2. The odd-ratio for mothers and daughters grows from 2.21 in 1976 to 4.14 in 1996 to 5.18 in 2011.

two-fifths of the mother-daughter association. Academic variables such as self-rated mathematics ability and personality, interest and goals play the largest role in mediating the mother-daughter association. This notable result warrants further inquiry.

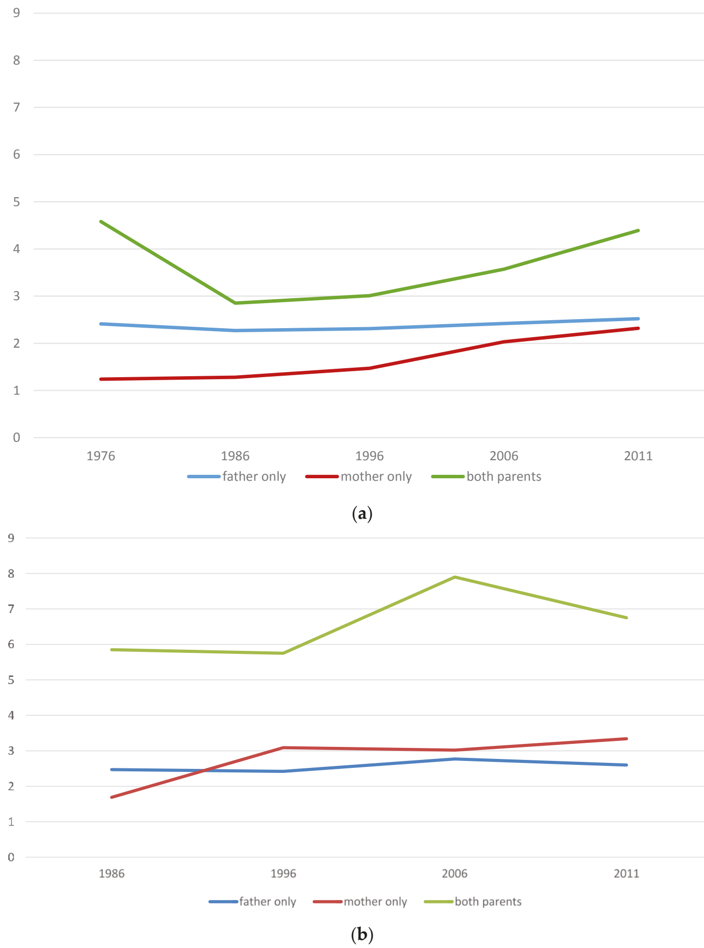

Figure 2. (**a**) Trends in Parent-Son Association for Plans to Enter Engineering: Odds Ratios; (**b**) Parent-Daughter Association for Plans to Enter Engineering: Odds Ratios.

The OLS analysis confirms the general story but there is less of a gendered difference in the effects of the mediating variables (See Table 4). The portion of the intergenerational association mediated by control variables is roughly 20% for fathers and sons, 25% for mothers and sons, 15% for fathers and daughters, and 20% for mothers and daughters. In both sets of specifications, there is a large intergenerational association not accounted for by the factors controlled in this analysis. The full regression models are reported below as Tables A3 and A4.

The results were estimated separately for freshman men and women. We pooled the two groups in order to test for statistical significance. Given the large sample sizes, the gender differences reported are all statistically significant, $p < 0.001$. Specifically, the father-son association differs from the father-daughter relationship, and the mother-son and mother-daughter effects differ as well.

Table 3. Summary of Logistic Regression Results.

A. Male Freshmen		Father			Mother		
		Engineer			Engineer		
		Coefficient	**Std. Error**	**Odds Ratio**	**Coefficient**	**Std. Error**	**Odds Ratio**
Model 0	Father Engineer, Mother Engineer	0.874	0.010	2.397	0.594	0.039	1.811
Model 1	Race, Ethnicity and Religion added	0.853	0.012	2.346	0.592	0.047	1.808
Model 2	Socio-economic Characteristics added	0.909	0.012	2.481	0.643	0.047	1.901
Model 3	Educational Preparation, Self-Rated Abilities and Aspirations added	0.866	0.013	2.378	0.582	0.050	1.790
Model 4	Personality, Interests and Goals added	0.798	0.014	2.220	0.533	0.053	1.704
Percent Parent Effect Unexplained (Model 0/Model 4)		91.30%		92.62%	89.73%		94.09%
No. of Cases		748,817					

B. Female Freshmen		Father			Mother		
		Engineer			Engineer		
		Coefficient	**Std. Error**	**Odds Ratio**	**Coefficient**	**Std. Error**	**Odds Ratio**
Model 0	Father Engineer, Mother Engineer	0.993	0.018	2.7	1.177	0.052	3.245
Model 1	Race, Ethnicity and Religion added	0.973	0.022	2.645	0.962	0.061	2.618
Model 2	Socio-economic Characteristics added	0.927	0.022	2.528	0.914	0.061	2.493
Model 3	Educational Preparation, Self-Rated Abilities and Aspirations added	0.817	0.023	2.264	0.772	0.065	2.164
Model 4	Personality, Interests and Goals added	0.75	0.024	2.116	0.715	0.068	2.043
Percent of Parent Effect Unexplained (Model 0/Model 4)		75.53%		78.37%	60.75%		62.96%
No. of Cases		885,793					

Note: Full Model is presented as Table A3.

Table 4. Summary of OLS Regression Results.

A. Male Freshmen		Father Engineer B	Father Engineer Std.	Mother Engineer B	Mother Engineer Std. Error	Adjusted R2
Model 0	Father Engineer, Mother Engineer	0.137	0.001	0.107	0.004	0.013
Model 1	Race, Ethnicity and Religion added	0.138	0.001	0.105	0.004	0.016
Model 2	Socio-economic Characteristics added	0.144	0.001	0.111	0.004	0.018
Model 3	Educational Preparation, Self-Rated Abilities and Aspirations added	0.126	0.001	0.094	0.004	0.094
Model 4	Personality, Interests and Goals added	0.11	0.001	0.081	0.004	0.150
Percent Parent Effect Unexplained (Model 0/Model 4)		80.20%		75.70%		
	No. of Cases			748,817		
B. Female Freshmen		**Father Engineer B**	**Father Engineer Std.**	**Mother Engineer B**	**Mother Engineer Std. Error**	**Adjusted R2**
Model 0	Father Engineer, Mother Engineer	0.038	0.001	0.079	0.003	0.006
Model 1	Race, Ethnicity and Religion added	0.040	0.001	0.073	0.003	0.008
Model 2	Socio-economic Characteristics added	0.039	0.001	0.072	0.003	0.008
Model 3	Educational Preparation, Self-Rated Abilities and Aspirations added	0.034	0.001	0.065	0.003	0.041
Model 4	Personality, Interests and Goals added	0.032	0.001	0.061	0.003	0.060
Percent Parent Effect Unexplained (Model 0/Model 4)		84.20%		77.20%		
	No. of Cases			885,793		

10. Persistence in Engineering

A skeptic might question whether freshman intentions are a meaningful indicator of the choice of major and career. While many students who report engineering as a career goal will not end up as engineers, the freshman data are more predictive than a questioning reader might assume. Moreover, if there is one field where the link between freshman intentions and career outcomes is likely to be evident, it would be the field of engineering. Many students enter the engineering pipeline early because the extensive and demanding requirements can make switching in relatively difficult. In fact, nearly all students who report planning to become an engineer also report that engineering is their intended field of study (95% of men and 94% of women). Thus, engineering career plans have face validity in terms of their connection to the choice of major.

A variety of data sources also suggest substantial persistence; that is, students who plan to major in engineering are well represented among those who graduate with engineering degrees and begin their careers as engineers. Astin and Astin (cited as [22] above) report that 43.9% of freshmen who intended to major in engineering in 1985 remained in the field four years later, and a total of 53.4% ended up in a STEM field. While this may seem to indicate a low rate of persistence, it should be noted that relatively few students switch into engineering. In other words, over two-thirds (68.9%) of those who were majoring in engineering in 1989 had planned to do so four years earlier. Expressed in terms of an odds ratio, students were 33 times more likely to become an engineering major if they had indicated this plan as a freshman.

A strong pattern of persistence of freshmen in engineering is also reported with more recent data by Hughes and his colleagues ([29] above). They also found that having a parent who was an engineer increased the chances of completing this course of study. In other words, having a parent who was an engineer not only increased the chances of entering engineering, but also increased the chances of continuing in the field. Sax [70] reports that the majority of engineering undergraduates who pursued graduate training (64.9% of women and 63.5% of men) did so in the field of engineering.

While the persistence data discussed here may seem to set a higher bound on the degree of parental impacts, there are a number of additional considerations that should be taken into account. It may be that some children of engineers who did not express an interest in the field reverted to this choice at some later point. As noted above, nearly one-third of engineering graduates switch into the field during college. If children of engineers are disproportionately represented in this group, it would increase the degree of intergenerational connection.

Another consideration has to do with near misses. It is often the case that children are affected by their parent's occupation even when it is not a case of complete correspondence. For example, if the mother is an electrical engineer and her daughter planned to be a computer scientist, many would consider this a case of the daughter following in her mother's footsteps, but in our analysis, this would be considered a defection [71]; see also [22]. If we add physical sciences and mathematics as additional educational choices and science-related careers, the extent of parental sway would be substantially higher than if the analysis is restricted to perfect matches.

11. Conclusions

This study contributes to our understanding of how the scientific and technical labor force is created. Specifically, there is a significant inter-generational association in the pursuit of careers in engineering. Both fathers and mothers significantly affect the career choices of their sons and daughters. These effects are large direct effects, that is, they are principally effects that are in addition to the effects of parents' socio-economic status and the influence that they may have on their children's values. In other words, the parental coefficients remain large even in full model with extensive controls.

Since young women and young men are roughly equally likely to have parents who are engineers, the gender differential in this case is not a matter of daughters' deficit. In other words, the gaps documented here are more about differences in parental effects between young men and young women rather than differences in levels of family resources or family exposure to engineering role models.

The data point to gender-specific role model effects. Sons are more likely to follow in their father's footsteps than in their mother's. The gender gap in parents' effects has narrowed as the salience of mothers on the career choices of their children has grown over time. The gender-specific role-modeling pattern for daughters is a story of change over time. In the 1970s and 1980s, daughters were more likely to follow their fathers than their mothers. However, since the 1990s, the mother-daughter connection has become stronger than the father-daughter connection. This pattern is most evident when the power of mothers is isolated by distinguishing mother-only engineering families from those in which both parents were engineers. Identifying the small numbers of families in which both parents are engineers reveals the powerful role modeling that occurs under such conditions.

Our results extend the findings of Sikora and Propokek [21] by showing that gender-specific parental role modeling operates at the point of college entry. The findings extend Marks's [62] analysis by examining occupation-specific role modeling effects. In other words, while the general socio-economic standing of mothers and fathers does not consistently appear to be channeled via gender-specific role modeling, the choice of specific occupations does operate in this manner. The results presented here run somewhat counter to those of Hellerstein and Morrill [64], in that it is the growing importance of mothers rather than fathers that stands out.

The daughters of engineers are much less likely than are sons to pursue careers in engineering. This gendered baseline is clear from the data, even though the presence of parents in the field leads daughters to pursue engineering far more than the classmates in non-engineering families. One potential source of additional women in engineering (and, by extension, other STEM fields) would be to increase their representation to the same level as their brothers and other male counterparts.

The results point to a growing effect of mothers on the career choices of their children, especially their daughters. We interpret this as pointing to a growing salience. The presence of mothers in the labor force is now more established, and mothers are working for a greater share of their children's early years. The evidence from engineering, which remains a majority-male field, brings the influence of mothers' careers into sharp relief.

The findings on the increasing impact of mothers on daughters is a promising development, but (a) engineering mothers remain relatively scarce, and thus the payoff of this relationship will take a long time to have a significant impact; and (b) the growing significance of mothers is relative to the low baseline of daughters' interest in engineering. In other words, while the impact of mothers is now considerable, the level of their daughters' interest in engineering continues to lag well behind their male counterparts.

Do the findings on the salience of parents' careers point to any policy recommendations for non-engineering families? Compared to students whose parents are engineers, other students have less direct exposure to the profession, less familiarity with the values and lifestyle that this type of career involves, and possibly less occupation-specific knowledge. Consequently, more effort to cultivate interest in engineering in these families is likely to be required.

The notion of gender-specific role models may perhaps be extended from the realm of family members to non-family members. Projects engaged in promoting women's representation in engineering [72] have tried to develop social supports in just this way. In other words, if students have not had direct exposure to engineering and related STEM fields in their own family experience, educators can seek to substitute other social experiences that would provide a substitute for this type of direct familiarity and exposure. The data reported here are consistent with the thrust of this type of non-familial social supports are in order for the great majority of college students who did not happen to have parents who spent their careers in the engineering profession.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Details on the Multivariate Regression Analysis

This study utilizes data from the Cooperative Institutional Research Program (CIRP) Freshman Survey, the oldest and largest longitudinal study of American higher education. The survey is administered to entering college students and covers a wide range of topics, including demographic background, high school experiences, college expectations, self-concepts, values, and life goals as well as their academic and career aspirations. A large number of these variables have been asked consistently over the years; hence, this information enables us to meet the study's key objectives, which is to examine changes over time in parent's influence on the pursuit of a career in engineering.

This study is based on CIRP data from 1225 baccalaureate-granting institutions from 1976 to 2011. Data on five time points (1976, 1986, 1996, 2006 and 2011 are included. The trend analysis explores how the intent to pursue a career in engineering has varied by gender from 1976 to 2011. The sample for the descriptive trend analysis was then weighted by student gender and institutional control, type, and selectivity so that it would reflect the population of first-time, full-time college students at all four-year institutions in the United States for each year. (See Pryor et al. [65], for a weighting scheme, in addition to validity, and reliability).

The regression analyses provide insight into the pathways which may account for parents' effect on their children's plans to pursue a career in engineering, and focus on five specific years of survey data: 1976, 1986, 1996, 2006, and 2011. These years were selected because they contained the most consistent set of survey items at evenly-spaced decade (and one half-decade) intervals. The regression sample from across these five years is unweighted.

1. Measures

Men's and women's self-reported plans to pursue a career in engineering (versus all other majors) serves as the dependent variable in the regression analysis. Planning a career in engineering is coded as 1 and all other career plans are coded as zero. Overall, 14.5% of the male freshmen and 1.9% of the female freshmen indicated that they planned to pursue careers in engineering. Given the focus on intergenerational connections, father's and mother's employment in engineering serve as the key independent variables in this analysis.

The list of independent variables used for the regression analysis, along with their coding schemes, is provided in Table A1.

Table A1. Variable List and Coding.

Dependent Variables	
Intent to Puruse a Career in Engineering	Dichotomous: 0 = All others, 1 = Engineering
Key Independent Varaiables	
Father Engineer	Dichotomous: 0 = All Others, 1 = Engineering
Mother Engineer	Dichotomous: 0 = All Others, 1 = Engineering
Race, Ethnicity and Religion Race (vs. White)	
African American	Dichotomous: 0 = "No", 1 = "Yes"
Asian American	Dichotomous: 0 = "No", 1 = "Yes"
Latino/Chicano	Dichotomous: 0 = "No", 1 = "Yes"
Native American	Dichotomous: 0 = "No", 1 = "Yes"
Religion: Catholic	Dichotomous: 0 = "No", 1 = "Yes"
Religion: Jewish	Dichotomous: 0 = "No", 1 = "Yes"
Religion: Other	Dichotomous: 0 = "No", 1 = "Yes"
Religion: None	Dichotomous: 0 = "No", 1 = "Yes"
Socio-Economic Characteristics	
Father's Education	8-point scale: 1 = "Grammar school or less" to 8 = "Graduate Degree"
Mother's Education	8-point scale: 1 = "Grammar school or less" to 8 = "Graduate Degree"
Family Income	25-point scale: 1 = "less than $6000" to 25 = "$250,000 or more"
Concern about Finances	3-point scale: 1 = "None", 2 ="Some", 3 = "Major"

Table A1. *Cont.*

Dependent Variables	
Educational Preparation, Self-Rated Abilities, and Aspirations	
High School GPA (Average grade in H.S.)	8-point scale: 1 = "D" to 8 = "A or A+"
Self-rated Mathematical Ability	5-point scale: 1 = "Lowest 10%" to 5 = "Highest 10%"
Future Activity: Make at least a 'B' average	4-point scale: 1 = "No Chance" to 4 = "Very Good Chance"
Future Activity: Change Major Field	4-point scale: 1 = "No Chance" to 4 = "Very Good Chance"
Degree Aspirations (vs. Bachelor's or less)	
Ph.D	Dichotomous: 0 = All Others, 1 = PhD
Law	Dichotomous: 0 = All Others, 1 = Law
Medical Degree	Dichotomous: 0 = All Others, 1 = Medical
Master's Degree/M.Div.	Dichotomous: 0 = All Others, 1 = Master's or M.Div.
Personality, Interests and Goals	
Leader Personality Factor	See Table A2
Scholar Personality Factor	See Table A2
Goal: Develop a meaningful philosophy of life	4-point scale: 1 = "Not Important" to 4 = "Essential"
Goal: Make a theoretical contribution to science	4-point scale: 1 = "Not Important" to 4 = "Essential"
Goal: Raise a family	4-point scale: 1 = "Not Important" to 4 = "Essential"
Social Activist Personality Factor	See Table A2
Artistic Personality Factor	See Table A2
Status Striver Personality Factor	See Table A2
Education Reasons for choosing a College Factor	See Table A2
Extrinsic Reasons for choosing a College Factor	See Table A2

2. Factor Analysis Procedures

Exploratory factor analysis using Principal Axis Factoring with Promax rotation was conducted to determine what factors would be used for the regression analysis. Factor analysis was guided by previously constructed factors from Astin's model of student types [73] as well as Sax's [74] typology and college choice factors. Of the 65 independent variables considered, forty-one variables were grouped into seven factors. (See Table A2 for a list of factors, their loadings, and reliability). The threshold for reliability was set at a Cronbach's *alpha* of 0.65, and variables were only considered valid for inclusion in a factor if they loaded at .40 or higher (ultimately, all loadings exceeded 0.60).

Table A2. Factor Variables, Loadings, and Reliabilities.

Factor	Factor Loading	
	Men	Women
Leader Personality	$\alpha = 0.66$	$\alpha = 0.65$
Self Rating: Drive to Achieve	0.72	0.71
Self-Rating: Leadership Ability	0.83	0.83
Self-Rating: Self-confidence (social)	0.77	0.75
Scholar Personality	$\alpha = 0.64$	$\alpha = 0.64$
Self-rated: Academic ability	0.80	0.79
Self-rated: Self-confidence (intellectual)	0.78	0.78
Self-rated: Writing ability	0.72	0.73
Social Activist Personality	$\alpha = 0.76$	$\alpha = 0.72$
Goal: Influence social values	0.77	0.74
Goal: Participate in a community action program	0.76	0.75
Goal: Help others in difficulty	0.65	0.61
Goal: Influence the political structure	0.72	0.69
Goal: Becoming involved in programs to clean up the environment	0.67	0.64
Artistic Personality	$\alpha = 0.72$	$\alpha = 0.69$
Goal: Create artistic work	0.83	0.82
Self-rated: Artistic ability	0.66	0.72
Goal: Write original works	0.75	0.67
Goal: Become accomplished in the performing arts	0.73	0.66

Table A2. *Cont.*

Factor	Factor Loading	
	Men	Women
Status Striver Personality	α = 0.64	α = 0.64
Goal: Obtain recognition from colleagues	0.78	0.78
Goal: Be very well-off financially	0.64	0.64
Goal: Become authority in my field	0.75	0.74
Goal: Be successful in a business of my own	0.62	0.62
Education Reasons for Choosing College	α = 0.63	α = 0.60
Reason: To gain a general education and appreciation of ideas	0.79	0.76
Reason: To make me a more cultured person	0.78	0.77
Reason: Learn more about things that interest me	0.73	0.73
Extrinsic Reasons for Choosing College	α = 0.67	α = 0.66
Reason: To be able to get a better job	0.87	0.86
Reason: To be able to make more money	0.87	0.86

3. Data Analysis

We included two dummy variables for parents' employment in engineering (father engineer = 1 if the student reports that the father is employed as an engineer, 0 otherwise; and mother engineer = 1 if the mother is an employed as an engineer, 0 otherwise). The baseline mode includes just these two intergenerational measures. We then added all other variables to assess whether the effect of the parental measures was mediated by other factors.

A set of 30 variables was categorized into four blocks. Variables were added in groups in order. The groups included: (1) race, ethnicity and religion; (2) socio-economic characteristics; (3) learning experiences, self-rated abilities, and educational aspirations; and (4) personality, interests and goals.

The key regression findings are summarized in the results section above. The full regression analyses are presented below as Table A3 (logistic regressions) and Table A4 (OLS regressions). While Mood has raised concerns about the interpretation of logistic regression coefficients, in this particular case the OLS and logistic findings are quite similar. We correlated the OLS and logistic coefficients across the 31 variables in the model. The association is extremely closely for men (Pearson's r = 0.98) and nearly as close for women (r = 0.90). The signs and directions of the coefficients are consistent across the OLS and logistic specifications.

There are many interesting coefficients in these analyses that are not the principal focus of this paper. Selected findings of note include the following. Women who plan to have a family by age 30 are less likely to plan a career in engineering, while the same goal does not deter young men. Self-rated ability in mathematics substantially increases the chances of expressing interest in a career in engineering for both men and women, as does interest in making a contribution to science. Interest in developing a meaningful philosophy of life, and factor scores for status striving, social activism are all negatively related to planning a career in engineering. The leadership factor has a negative sign for men but not statistically significant for women. These results are consistent with those found in previous studies of engineering and STEM majors.

The key finding that we stress in this paper is the effect of father's and mother's employment in engineering. This effect continues to be statistically significant in the final model, even after race, ethnicity, religion and other socio-economic factors are controlled. The parental effect is partially mediated by educational plans and values for men and somewhat more so for women, but the clear majority of the parental effect remains even after all of these variables are taken into account.

Table A3. Logistic Regression Results: Final Model.

Logistic Regression											
Male Freshman						Female Freshman					
Variables in the Equation						Variables in the Equation					
	B	S.E.	Wald	Sig.	Exp(B)		B	S.E.	Wald	Sig.	Exp(B)
FC_Engineering	0.798	0.014	3253.312	0.000	2.220	FC_Engineering	0.750	0.024	995.666	0.000	2.116
MC_Engineering	0.533	0.053	100.838	0.000	1.704	MC_Engineering	0.715	0.068	110.360	0.000	2.043
YEAR	−0.140	0.004	1314.186	0.000	0.869	YEAR	−0.073	0.008	91.981	0.000	0.930
Dummy: Asian	0.123	0.020	38.582	0.000	1.131	Dummy: Asian	0.370	0.033	126.825	0.000	1.448
Dummy: Black	0.468	0.023	397.921	0.000	1.597	Dummy: Black	0.954	0.037	676.325	0.000	2.595
Dummy: Latino	0.293	0.027	120.172	0.000	1.341	Dummy: Latino	0.701	0.046	234.301	0.000	2.017
Dummy: Other including American Indian and Multi	0.118	0.021	32.486	0.000	1.125	Dummy: Other including American Indian and Multi	0.346	0.036	93.266	0.000	1.413
SReligion: Catholic	0.065	0.011	33.828	0.000	1.067	SReligion: Catholic	0.208	0.022	92.528	0.000	1.231
SReligion: Jewish	−0.655	0.031	440.840	0.000	0.519	SReligion: Jewish	−0.371	0.062	35.398	0.000	0.690
SReligion: Other	0.008	0.019	0.155	0.694	1.008	SReligion: Other	0.109	0.036	9.278	0.002	1.115
SReligion: None	−0.121	0.014	76.915	0.000	0.886	SReligion: None	0.100	0.027	14.016	0.000	1.105
Father's education	−0.028	0.003	83.533	0.000	0.973	Father's education	0.029	0.006	25.030	0.000	1.030
Mother's education	0.006	0.003	2.944	0.086	1.006	Mother's education	0.034	0.006	30.665	0.000	1.035
Income quintiles	−0.043	0.004	106.034	0.000	0.958	Income quintiles	0.032	0.008	15.560	0.000	1.032
Do you have any concern about your ability to finance your college education?	0.040	0.008	26.592	0.000	1.040	Do you have any concern about your ability to finance your college education?	0.025	0.015	2.884	0.089	1.025
What was your average grade in high school?	0.167	0.004	1958.951	0.000	1.181	What was your average grade in high school?	0.272	0.009	923.098	0.000	1.313
Self Rating: Mathematical ability	0.747	0.007	13025.082	0.000	2.111	Self Rating: Mathematical ability	1.096	0.013	7512.946	0.000	2.992
Future Act: Make at least a 'B' average	−0.081	0.009	88.221	0.000	0.922	Future Act: Make at least a 'B' average	−0.239	0.017	207.048	0.000	0.787
Degree Asp: Ph.D.	−0.523	0.015	1154.369	0.000	0.593	Degree Asp: Ph.D.	−0.231	0.029	62.641	0.000	0.794
Degree Asp: Med.	−3.136	0.037	7165.405	0.000	0.043	Degree Asp: Med.	−2.416	0.053	2079.808	0.000	0.089
Degree Asp: Masters non Med.	−0.002	0.011	0.022	0.883	0.998	Degree Asp: Masters non Med.	0.204	0.023	75.724	0.000	1.226
Leader: REGR factor score	−0.048	0.006	73.898	0.000	0.953	Leader: REGR factor score	0.007	0.011	0.407	0.523	1.007
Goal: Developing a meaningful philosophy of life	−0.053	0.006	91.881	0.000	0.948	Goal: Developing a meaningful philosophy of life	−0.038	0.011	13.172	0.000	0.962
Goal: Making a theoretical contribution to science	0.780	0.006	17383.451	0.000	2.182	Goal: Making a theoretical contribution to science	0.830	0.010	6592.794	0.000	2.293
Goal: Raising a family	0.054	0.005	96.431	0.000	1.055	Goal: Raising a family	−0.121	0.010	159.509	0.000	0.886
Scholar: REGR factor score	−0.216	0.007	1084.228	0.000	0.806	Scholar: REGR factor score	−0.098	0.013	60.751	0.000	0.907
Social Activism: REGR factor score	−0.320	0.006	2524.803	0.000	0.726	Social Activism: REGR factor score	−0.256	0.012	455.184	0.000	0.774
Artistic: REGR factor score	−0.182	0.006	919.841	0.000	0.834	Artistic: REGR factor score	−0.190	0.011	290.775	0.000	0.827
Status Striver: REGR factor score	−0.153	0.006	699.422	0.000	0.858	Status Striver: REGR factor score	−0.123	0.011	125.711	0.000	0.884
Ed Reasons:REGR factor score	−0.057	0.005	137.500	0.000	0.944	Ed Reasons:REGR factor score	−0.107	0.010	106.263	0.000	0.898
Ex Reasons: REGR factor score	0.305	0.006	2646.099	0.000	1.356	Ex Reasons: REGR factor score	0.253	0.011	532.042	0.000	1.288
Constant	−6.311	0.050	15776.190	0.000	0.002	Constant	−10.245	0.107	9090.693	0.000	0.000

Table A4. OLS Regression Results, Final Model.

Male Freshmen					
Coefficients					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	−0.274	0.005		−54.463	0.000
FC_Engineering	0.11	0.002	0.087	61.839	0.000
MC_Engineering	0.081	0.007	0.016	11.485	0.000
YEAR	−0.015	0	−0.06	−37.385	0.000
Dummy: Asian	0.007	0.002	0.005	3.262	0.001
Dummy: Black	0.041	0.003	0.024	16.587	0.000
Dummy: Latino	0.029	0.003	0.014	9.832	0.000
Dummy: Other including American Indian and Multi	0.012	0.002	0.008	5.525	0.000
Religion: Catholic	0.007	0.001	0.009	6.004	0.000
Religion: Jewish	−0.05	0.003	−0.028	−19.144	0.000
Religion: Other	0.002	0.002	0.001	0.946	0.344
Religion: None	−0.008	0.001	−0.008	−5.121	0.000
Father's education	−0.003	0.000	−0.016	−8.553	0.000
Mother's education	0.001	0.000	0.004	2.058	0.040
Income quintiles	−0.004	0.000	−0.016	−9.791	0.000
Do you have any concern about your ability to finance your college education?	0.005	0.001	0.009	6.104	0.000
What was your average grade in high school?	0.018	0.000	0.082	46.971	0.000
Self-Rating: Mathematical ability	0.067	0.001	0.185	112.229	0.000
Future Act: Make at least a 'B' average	−0.005	0.001	−0.009	−5.641	0.000
Degree Asp: PhD	−0.048	0.002	−0.05	−28.704	0.000
Degree Asp: Med	−0.227	0.002	−0.191	−114.528	0.000
Degree Asp: Masters non Med	0.004	0.001	0.005	2.785	0.005
Leader: REGR factor score	−0.007	0.001	−0.021	−12.347	0.000
Goal: Developing a meaningful philosophy of life	−0.005	0.001	−0.014	−8.374	0.000
Goal: Making a theoretical contribution to science	0.091	0.001	0.227	141.784	0.000
Goal: Raising a family	0.005	0.001	0.012	8.029	0.000
Scholar: REGR factor score	−0.016	0.001	−0.043	−22.606	0.000
Social Activism: REGR factor score	−0.035	0.001	−0.098	−54.135	0.000
Artistic: REGR factor score	−0.017	0.001	−0.047	−30.235	0.000
Status Striver: REGR factor score	−0.015	0.001	−0.04	−24.457	0.000
Ed Reasons: REGR factor score	−0.006	0.001	−0.017	−11.117	0.000
Ex Reasons: REGR factor score	0.026	0.001	0.072	47.36	0.000

Female Freshmen					
Coefficients [a]					
Model	Unstandardized Coefficients		Standardized Coefficients	t	
	B	Std. Error	Beta	Sig.	Sig.
(Constant)	−0.106	0.002		−43.884	0.000
FC_Engineering	0.032	0.001	0.053	38.261	0.000
MC_Engineering	0.061	0.003	0.027	19.328	0.000
YEAR	−0.002	0.000	−0.014	−9.024	0.000
Dummy: Asian	0.013	0.001	0.018	12.309	0.000
Dummy: Black	0.021	0.001	0.03	20.41	0.000
Dummy: Latino	0.017	0.001	0.019	13.246	0.000
Dummy: Other including American Indian and Multi	0.009	0.001	0.013	9.293	0.000
Religion: Catholic	0.005	0.001	0.012	8.148	0.000
Religion: Jewish	−0.006	0.001	−0.007	−4.85	0.000
Religion: Other	0.003	0.001	0.005	3.484	0.000
Religion: None	0.005	0.001	0.01	6.727	0.000
Father's education	0.001	0.000	0.012	6.465	0.000
Mother's education	0.001	0.000	0.011	5.982	0.000
Income quintiles	0.001	0.000	0.006	3.741	0.000
Do you have any concern about your ability to finance your college education?	0.001	0.000	0.003	2.291	0.022
What was your average grade in high school?	0.005	0.000	0.045	26.984	0.000
Self-Rating: Mathematical ability	0.023	0.000	0.137	88.259	0.000
Future Act: Make at least a 'B' average	−0.006	0.000	−0.021	−13.802	0.000
Degree Asp: PhD	−0.002	0.001	−0.005	−3.227	0.001
Degree Asp: Med	−0.058	0.001	−0.108	−64.568	0.000
Degree Asp: Masters non Med	0.006	0.001	0.017	9.95	0.000
Leader: REGR factor score	0.000	0.000	0.001	0.586	0.558
Goal: Developing a meaningful philosophy of life	−0.001	0.000	−0.005	−2.803	0.005
Goal: Making a theoretical contribution to science	0.029	0.000	0.146	94.044	0.000
Goal: Raising a family	−0.003	0.000	−0.02	−13.623	0.000
Scholar: REGR factor score	0.001	0.000	0.004	2.205	0.027
Social Activism: REGR factor score	−0.008	0.000	−0.047	−27.214	0.000
Artistic: REGR factor score	−0.005	0.000	−0.028	−18.442	0.000
Status Striver: REGR factor score	−0.002	0.000	−0.015	−9.177	0.000
Ed Reasons: REGR factor score	−0.003	0.000	−0.015	−9.999	0.000
Ex Reasons: REGR factor score	0.005	0	0.03	20.193	0.000

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social sciences

Article

Making STEM "Family Friendly": The Impact of Perceiving Science Careers as Family-Compatible

Erica S. Weisgram [1,*] and Amanda B. Diekman [2]

[1] Department of Psychology, University of Wisconsin-Stevens Point, Stevens Point, WI 54481, USA
[2] Department of Psychology, Miami University, Oxford, OH 45056, USA; diekmaa@miamioh.edu
* Correspondence: Erica.Weisgram@uwsp.edu

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Abstract: Two studies extended the communal goal congruity perspective to examine perceived incongruity between science careers and family caregiving goals. Study 1 examined beliefs about science careers among young adolescents, older adolescents, and young adults. Science careers were perceived as unlikely to afford family goals, and this belief emerged more strongly with age cohort. Study 1 also documented that the perception that science affords family goals predicts interest in pursuing science. Study 2 then employed an experimental methodology to investigate the impact of framing a science career as integrated with family life or not. For family-oriented women, the family-friendly framing of science produced greater personal favorability toward pursuing a science career. In addition, perceived fulfilment of the scientist described predicted personal favorability toward a science career path. We discuss the implications of these findings for research and for policy.

Keywords: gender; STEM; goal congruity; family

1. Introduction

Researchers across the disciplines of psychology, sociology, education, and many others offer an assortment of possible explanations for the underrepresentation of women in STEM (Ceci and Williams 2007; Diekman et al. 2015). Recent reviews have called for greater emphasis on the role of girls' and women's personal choice in the process of selecting a STEM career (Valla and Ceci 2014), along with an understanding of how these choices are influenced by both individual-level and structural-level factors (Diekman and Fuesting). The factors that influence girls' and women's personal choices often reflect gendered cultural beliefs, internalized gender stereotypes, and perceptions of gender bias by individuals and organizations. For example, individuals' assessments about their own skill within domains are influenced by gender stereotypic expectations (Correll 2001), and occupational structures do not readily integrate caregiving responsibilities that continue to be central to the female role (Stone 2007). Understanding how STEM occupations are perceived to afford family goals, and how these perceptions influence choice processes, is the purpose of the current research.

This research utilizes a goal congruity framework that suggests that a key factor influencing entry into social roles is the perceived alignment between those roles and the valued goals of the individual (Diekman et al. 2017). We extend the goal congruity framework that has been applied to communal goals and STEM interests (Diekman et al. 2010) to include family caregiving goals. Thus, we specifically focus on how perceptions of science careers as affording family goals—allowing one to spend time with one's family and care for one's family—impact individuals' interest in pursuing STEM pathways. We explore this research question across two studies. In Study 1, we investigate age and gender differences in children's, adolescents', and adults' perceptions of STEM careers as affording family goals and whether these perceptions predict interest in STEM careers. In Study 2, we use an experimental design to investigate the causal impact of perceptions that science careers afford family goals on young women's attitudes toward STEM careers.

1.1. The Goal Congruity Framework

The goal congruity approach posits that perceived congruity between individuals' goals and their social roles fosters positivity toward entering into and persisting in social roles (Diekman et al. 2017). Social roles function as an opportunity structure that people navigate in order to meet their valued goals (Diekman and Eagly 2008). Critically important is the recognition that in the goal congruity framework, *anticipated* incongruity between goals and roles is central. Even though anticipated incongruity may or may not align with *actual* incongruity, anticipated incongruity can affect decisions (Diekman et al. 2017). As we illustrate in the current research, the mere perception that STEM careers are incompatible with family goals can influence intentions to persist along those pathways, regardless of the accuracy of this perception.

The goal congruity model has documented robust, consensual stereotypes of STEM careers as less likely to afford communal goals than other kinds of careers (Diekman et al. 2010, 2011). Given these stereotypes, more communally-oriented individuals (who tend to be women; (Diekman et al. 2011; Schwartz and Rubel 2005)) are less likely to be interested in STEM careers (Diekman et al. 2010). However, individuals who do see STEM as affording communal goals express greater interest in STEM (Brown et al. 2015). Especially important is evidence demonstrating that beliefs about communal goal affordances in STEM are malleable. Interventions that frame science careers as affording altruistic and collaborative goals succeeded in increasing positivity toward STEM careers, particularly among young girls and women (Diekman et al. 2011; Weisgram and Bigler 2006).

To date, the goal congruity research has focused on communal goals as a broad construct, including a general orientation to help others or work with others. In the current work, we extend the goal congruity approach to consider the endorsement of family goals, and the perception that STEM fields allow one to meet family goals (Weisgram and Diekman 2016). Although the endorsement of family goals could be seen as an extension of communal goals in that family caregiving also is other-oriented (Weisgram et al. 2011), people who endorse communal goals may or may not also endorse family goals—the desire to have a family and spend time caretaking for their family members. Thus, research is needed to investigate specifically how perceived congruity or incongruity of family goals influences women's and men's and STEM interests and attitudes.

1.2. The Importance of Family

In the social, vocational, and developmental psychology literatures, research has demonstrated that caring for one's future family is a high priority for both men and women (Konrad et al. 2000; Weisgram and Hayes 2014). However, gender differences in family goal endorsement also emerge, with women endorsing family goals more than men (Weisgram et al. 2010, 2011). This gender difference is not present in childhood and adolescence, but emerges in young adulthood as men and women begin to consider their future more closely (Weisgram et al. 2010). This increasing gender difference may also be due to increasing influence of gender norms with age. Moreover, men and women encounter different opportunities to pursue and display their family-oriented values: because family orientation is more central to the female gender role, others may elicit more expectancy-confirming behavior and attitudes (Geis 1993), resulting in greater expression of family goals by women than men.

However, men and women may have different perspectives on what caring for one's family entails, perhaps stemming from the traditional breadwinner-caregiver model (Fulcher and Coyle 2011; Fulcher et al. 2015). Women may see themselves as caring for their family by taking time off from their careers, being home with their children, and providing physical and emotional care; and men may see themselves as caring for their family by providing income for housing, food, and other expenses (Brown and Diekman 2010; Curry et al. 1994). These gendered perspectives may have educational and occupational consequences as adolescents and adults make achievement-related choices. Indeed, for women, two competing cultural schemas—devotion to work and devotion to family—can be seen as wholly impossible to pursue simultaneously (Blair-Loy 2009). These presumed tradeoffs emerge in educational and career expectations: among adolescents, endorsing traditional attitudes about work-family gender roles predicted lower educational expectations (i.e., only graduating high school), while endorsing egalitarian attitudes predicted higher educational expectations (i.e., attending college or graduate school; (Davis and Pearce 2007)). Among undergraduate college students, valuing family goals predicted higher anticipated pay for men and lower work commitment and anticipated pay for women (Lips and Lawson 2009).

In general, gendered ideas about caring for one's family may lead women to negotiate flexible work roles or take time off from work altogether (Fulcher et al. 2015). If flexible options are not available, women may opt out of a particular career: for example, women who leave a male-dominated field for a female-dominated field often cite family reasons (Frome et al. 2006). Given the current workplace structure and traditional gender role expectations, women may be more likely than men to project explicit trade-offs between work and family. For example, traditionally college-aged men and women project gender-differentiated possible selves ten years into the future (Curry et al. 1994). In particular, women who rated their family selves as highly relevant were less likely to rate their career selves as relevant. Other research has shown a negative correlation between the importance of and commitment to work and importance of and commitment to family among women, but not among men (Owen Blakemore et al. 2005; Friedman and Weissbrod 2005). Although both men and women appear to value family involvement, this involvement is projected to be in opposition to paid work for women, but not for men. In general, the ability to balance work and life is related to a sense of life fulfilment and satisfaction for men and women (Greenhaus et al. 2003; Gröpel and Kuhl 2009), but how men and women combine work and life may differ.

As men and women explore their career options and then enter the world of work and parenthood, their endorsement of family goals may change. Across the 10 years following graduate school entry, women in STEM fields, particularly those with children, significantly increased their preference for a job that was flexible, had weekends free, and had reasonable hours (less than 50 hours per week); in contrast, these preferences stayed the same for men across the same time period (Ferriman et al. 2009). Indeed, 40% of women with children felt that working part-time was very important, whereas fewer than 15% of men agreed. These family orientations have been shown to negatively predict young women's (and young men's) interest in Computer Science (Beyer 2014)—a finding that may generalize to other STEM fields as well.

A key point is that presumed incongruity between career and family goals can influence decisions, even if individuals are unaware of this influence. For example, in interviews with 100 students at multiple campuses, Cech found that neither male nor female students considered their family plans as important in their career decisions (Cech 2016). Some comments also reflected a sense that their career paths would accommodate their family goals, reflecting the value they accorded to work-family alignment. The questions we pose in the current research are: (1) are STEM fields in particular perceived as posing challenges to integrating family; and (2) do models of scientists who integrate or do not integrate family influence women's positivity toward pursuing science? We thus first turn to the literature that suggests that STEM careers are often perceived to impede engaging in family caregiving (Weisgram and Diekman 2016).

1.3. Perceptions of STEM Careers as "Family-Unfriendly"

According to the goal congruity approach, the perception of STEM careers as affording the opportunity to attain family goals is key to the recruitment of family-oriented men and women into the field. However, research by Weisgram et al. suggests that individuals (children, adolescents, and young adults) perceive masculine jobs, in general, as affording family goals to a lesser extent than feminine jobs (Weisgram et al. 2010). Importantly, the study also reported adults' ratings of family goal affordances for individual occupations. Indeed, the job of "scientist" (M = 2.16, SD = 0.74) was rated lower in affording family goals than masculine jobs (*M* = 2.51, *SD* = 0.32) and feminine jobs (*M* = 3.07, *SD* = 0.40).

There are several reasons that STEM jobs may be perceived as being family "un-friendly." One reason may be the overall stereotype of scientists: young adults perceive successful scientists to be less communal and more agentic than men and women in general (Carli et al. 2016). Indeed, parents are perceived as less agentic, and less committed to potential jobs, than nonparents (Fuegen et al. 2004). Thus, it may be that perceptions of successful scientists are at odds with perceptions of successful parents.

Beliefs about perceived affordances of roles can be rooted in a range of prior experience with the role (Diekman et al. 2017). The cues to perceptions of whether science affords family goals can thus come from either primary or secondary experience. Primary experience might include science activities or classes, or interactions with scientists. As students approach college, they are increasingly likely to have more first-hand contact with scientists (rather than science educators); however, these members of the science faculty may actually reinforce perceptions that science careers do not align with family caregiving goals. First, there are fewer women than men in academic science and engineering positions (National Science Board 2016); second, those female scientists who are in academia may not disclose information about their family caregiving responsibilities, given that these are not normative within the profession. Thus, as students move from childhood to emerging adulthood, they may be exposed to more information that confirms, rather than disconfirms, perceptions that science does not afford family goals.

Perceptions of scientists and their work may also develop based on media depictions of scientists. Because children, adolescents, and adults may not interact personally with scientists in their everyday life, presentations of scientists in books, television, and movies influence individuals' perceptions of both scientists and STEM careers (Steinke et al. 2007). Representation of science as integrated with family caregiving is rare: For example, a content analysis of popular films found that of the 23 female scientists depicted, only four were depicted as mothers and of those, only two were depicted as full-time employed mothers (Steinke 2005). The lack of media models of scientists, especially female scientists, who combine family caregiving and career may contribute to children's, adolescents', and adults' perceptions of STEM careers being incompatible with spending time with and caring for family members.

Perceived challenges in combining STEM careers and family goals can result from a number of factors, including the type of training needed to attain STEM careers, the timing of advanced education or training opportunities, and discrimination based on parental status. Many professional fields include long hours and extensive training, such as law and medicine—fields that have a greater proportion of female workers than most STEM fields (48% of medical degrees and 47% of law degrees are awarded to women (National Center for Education Statistics 2011). Although many individuals move to STEM careers with a Bachelor's degree (i.e., jobs in industry), many jobs, including those within academia, require advanced degrees and have a particularly long period of apprenticeship before an individual secures a permanent position. Most academic scientists attend graduate school, followed by a post-doctoral apprenticeship (or two), and then enter a tenure-track position achieving tenure after six to seven years—a combined probationary period that often overlaps with the developmental time period in which many women wish to have children. In addition, the work of scientists often includes labor- and time-intensive work in the lab (e.g., chemistry, neuroscience) or in the field of study (e.g., biology, paleontology), and thus they may not be able to have a flexible schedule to accommodate children's needs, may need to travel to conduct fieldwork (perhaps to locations that are unsafe for children), travel to conferences to present and learn about current research, or may have to make decisions between attending to a time-sensitive research project (e.g., work with rats who reach puberty on a given day) and children's care (e.g., sick child care, special occasions at children's schools). Because of the perceived and real difficulties of combining an academic STEM job with family duties, many women elect to leave academic positions for STEM positions for positions in industry that have more reliable hours and often higher salaries (Newsome 2008).

Advocates for gender equality in STEM fields have recently argued that decreasing barriers to family commitments is key in recruiting and retaining women (Weisgram and Diekman 2016; Villablanca et al. 2011; Williams and Ceci 2012). Policies are present in many academic and non-academic workplaces that may decrease these barriers such as parental leave (paid or unpaid) or stopping a tenure clock. Women are more likely than men to want to use these policies but chose not to make a request to do so (Villablanca et al. 2011). Women were more concerned than men with the reaction of their colleagues for using family benefits. In addition, within a School of Medicine, women were more likely than men to report remaining childless or having fewer children than desired (Villablanca et al. 2011).

In surveys of both postdoctoral fellows and tenure-track faculty, the perception that an institution supports family responsibilities strongly predicts job satisfaction and workplace belonging (Heilbronner 2013). Among STEM postdocs and faculty (including medical sciences), this relationship was stronger for women than for men. In addition, surveys of men and women who left STEM careers often note that the incompatibility with family responsibilities strongly influenced their decision to leave (Heilbronner 2013).

The importance of gender balance and work-life interaction to individuals considering STEM careers was demonstrated in an experimental study (DeFraine et al. 2014). Undergraduate and graduate students who were highly identified with math watched one of two lab recruitment videos, which either depicted a male-dominated, work-focused environment that emphasized competition, or a gender-equal work/life-interaction-focused environment that emphasized flexibility and collaboration. Although commitment to science did not differ between the groups, those students, both men and women, who watched the work-life-interaction video projected that they would feel a greater sense of belonging in the lab and reported a greater desire to participate. Thus, depicting a research lab as allowing flexibility across work and home domains led to benefits. However, whether these benefits are specifically due to perceived family-friendliness, or are also due to the increased presence of women and increased collaboration, is a question that remains.

1.4. The Present Studies

The present studies examine the relationships between individuals' perceptions of science as affording family goals and their interest in science. In Study 1, we examine gender and developmental differences in interest in science and perceptions that science jobs afford family goals among three different age groups: young adolescents, older adolescents, and young adults. We also examine whether perceptions that science affords family goals predicts interest in science. In Study 2, we present an experiment that directly manipulates perception of science jobs as affording family goals and examines effects on women's interest in pursuing these roles. We focus on women in particular because of the underrepresentation of women in STEM fields and because of the perceived family-impacting-work conflict that young women anticipate relative to young men (Fulcher and Coyle 2011). Given the importance that men and women ascribe to family goals and the relatively little literature on the perception of STEM careers as affording these goals in relation to interest in STEM, these studies fill an important void in the literature.

2. Study 1

In Study 1, we examined gender and age differences in individuals' perceptions of science as affording family values and their relation to interest in science tasks and careers. This developmental timepoint is critical, as boys and girls begin to lose interest in STEM careers in adolescence, with boys retaining higher interest than girls across development (Frenzel et al. 2010). Research by Weisgram et al. has demonstrated that age differences, but not gender differences, emerge for the perception that masculine jobs afford family goals less than feminine jobs (Weisgram et al. 2010). Moreover, research with young adults has found consensus across male and female participants in beliefs that STEM fields lack communal opportunities (Diekman et al. 2010, 2011). We predict that family affordances of STEM jobs will also follow this pattern.

We expected to replicate robust gender differences in science interest with boys and young men reporting greater interest than girls and young women, and with gender differences increasing across age groups. We then sought to examine whether family goal affordances would predict interest in STEM. Specifically, we expected that the belief that science affords family goals will positively predict interest in science careers and science tasks.

2.1. Methods

2.1.1. Participants

Participants included 103 middle school adolescents (37 boys, 66 girls; M_{age} = 12.47, *SD* = 0.52), 80 high school adolescents (32 boys, 48 girls; M_{age} = 15.64, *SD* = 0.73), and 217 undergraduate students (92 men, 125 women; M_{age} = 19.49, *SD* = 1.34). Middle school (7th grade) and high school (10th grade) students were recruited from public schools in a mid-sized city in the Midwest. Science teachers recruited students from their classrooms with surveys administrated to each student who received parent permission. Undergraduate students were recruited from introductory psychology classes at a mid-sized regional university in the Midwest in the same city where the adolescent data were collected. Students completed the study as part of course participation. The sample was 88% European American, 4.5% Asian American, 2% African American, 2% Hispanic American, 1% Native American/Alaskan, 2.5% Other/Unreported, and is reflective of the region in which the data was collected. Parent permission was received for all adolescents in the sample.

2.1.2. Procedures

Participants completed three surveys: (a) perceptions of science; (b) interest in science careers, and (c) interest in science tasks. Adolescents completed paper and pencil versions of the survey during their mandatory science classes. Undergraduate students completed online versions of the same survey.

2.1.3. Measures

Perceptions of Science Jobs

To assess whether participants perceive science jobs as affording family values, participants answered four items derived from Weisgram and Bigler's Occupational Values Scale (Weisgram and Bigler 2006). Participants were given the prompt of "Being a scientist is a job that . . . " with sentence completions including "allows scientists to take time off when they become a parent," "allows scientists to easily manage both a career and a family," "gives scientists plenty of time to spend with their family," and "allows scientists to work part-time when their children are young." Response options ranged from (1) "Not at all" to (4) "Very Much." Reliability was high for each age group, with Cronbach alphas ranging from 0.78 to 0.88.

Interest in Science Careers

Interest in five science careers was assessed: scientist (general), astronomer, physicist, chemist, and biologist. A brief description of each career was given (e.g., "a physicist is someone who studies what things are made of (matter), energy, atoms, light, sound, x-rays, gravity, and many other aspects of the physical world"). Participants were asked how much they would want to do each job on a scale of (1) "Not at all" to (4) "Very Much." Reliability was high for each age group, with Cronbach alphas ranging from 0.68 to 0.80.

Interest in Science Tasks

Because many individuals are unaware of what science jobs entail or feel they are unable to commit to a science career, interest in scientific tasks was also assessed (Weisgram and Bigler 2006, 2007). This list of 25 scientific tasks was developed by Weisgram and Bigler in consultation with female scientists (Weisgram and Bigler 2006). Participants were asked to indicate how interested they were in performing each task with response options ranging from (1) "Not at all" to (4) "Very Much." Cronbach alphas ranged from 0.89 to 0.92 for the three age groups.

2.2. Results

Data analysis was a two-step process. First, we investigated age and gender differences on family affordances, interest in science careers, and interest in science tasks. Second, we examined whether beliefs that science afforded family goals predicted interest in science careers and science tasks.

2.2.1. Gender and Age Differences

For each construct, a 2 (gender: male, female) $\times$ 3 (age group: younger adolescents, older adolescents, college students) analysis of variance (ANOVA) was performed. As shown in Figure 1, the belief that science afforded family goals decreased with each age group, as reflected in the significant effect of age group, $F(1, 386) = 24.40$, $p < 0.001$, partial $\eta^2 = 0.11$. Post hoc comparisons (LSD) indicated that beliefs that science affords communal goals were held most by middle school students and least by college students, with each age group significantly differing from the others. No gender differences emerged for perceptions of science as affording family goals.

Consistent with past research, boys and young men reported greater interest in science careers and tasks than did girls and young women across all age groups. These differences were significantly different for science tasks, $F(1, 387) = 31.12$, $p < 0.001$, partial $\eta^2 = 0.11$, and marginally significant for science careers, $F(1, 386) = 3.34$, $p = 0.06$, partial $\eta^2 = 0.01$. See Table 1 for means and standard deviations.

Table 1. Study 1: Means and Standard Deviations for Dependent Variables by Gender and Age Group.

	Males							
	Middle School (*n* = 37)		**High School (*n* = 32)**		**College (*n* = 92)**		**Overall (*n* = 161)**	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Perception of Science as Affording Family Goals	3.03 [a]	0.71	2.81 [b]	0.77	2.40 [c]	0.49	2.63	0.67
Interest in Science Careers	2.13	0.52	2.07	0.85	2.11	0.68	2.11	0.69
Interest in Science Tasks	2.22	0.52	2.17	0.63	2.09	0.48	2.14	0.52
	Females							
	Middle School (*n* = 66)		**High School (*n* = 48)**		**College (*n* = 125)**		**Overall (*n* = 239)**	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Perception of Science as Affording Family Goals	2.95 [a]	0.77	2.65 [b]	0.63	2.51 [c]	0.55	2.66	0.66
Interest in Science Careers	2.11	0.60	1.95	0.56	1.85	0.67	1.94	0.64
Interest in Science Tasks	1.90	0.43	1.86	0.49	1.80	0.48	1.84	0.47

Note: All values range from 1 (low) to 4 (high). Superscripts indicate significant differences across groups.

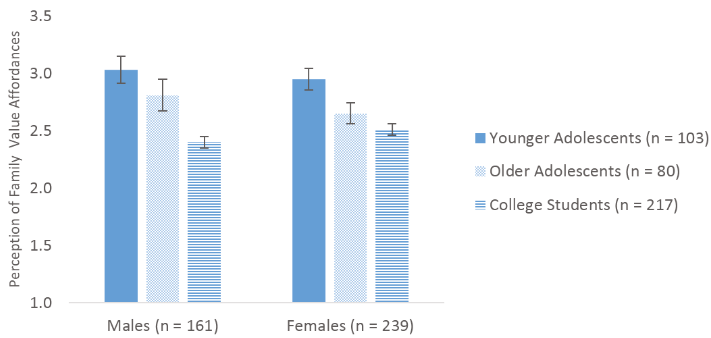

Figure 1. Perception that science affords family goals by gender and age group.

2.2.2. Predicting Science Interests

To examine whether interest in science careers and tasks was predicted by participants' perceptions of science as affording family goals, regression analyses were performed. Because there were significant age differences (but not gender differences) in perceptions that science affords family goals, age group was included as dummy variables with the middle school group representing the reference group. Perceptions that science affords family goals, and the interactions between this construct and the dummy variables, were included as predictor variables in the linear regressions. For interest in science tasks, perceptions that science careers afford family goals was a significant predictor (see Table 2). Results for interest in science careers followed a similar pattern (see Table 2).

Table 2. Study 1: Predictors of Interest in STEM Careers and Tasks

	Standardized Beta Values
Interest in Science Tasks	$F(3, 388) = 13.89$, $p < 0.001$, $R^2 = 0.10$
Perceptions of STEM as affording family goals	0.30 *
Age group (high school = 1) × Perceptions	0.06
Age group (college = 1) × Perceptions	0.05
Interest in Science Careers	$F(3, 387) = 4.60$, $p = 0.004$, $R^2 = 0.03$
Perceptions of STEM as affording family goals	0.19 *
Age group (high school = 1) × Perceptions	−0.02
Age group (college = 1) × Perceptions	−0.02

Note: * $p < 0.05$.

2.3. *Discussion*

Study 1 provided a novel examination of whether students from middle school through college perceive science as affording opportunities to have a family life. We assessed gender and age differences and in perception that STEM careers afford goals and also examined the predictive relationship between beliefs that science affords family goals and interest in science tasks and careers. Results showed a clear developmental trend in the perception that a career in science affords family goals; although middle schoolers endorse these beliefs to a moderate extent, high school students are less likely to hold these beliefs, and college students are even less likely than their younger counterparts.

To our knowledge, this study is the first to document age trends in perceptions of whether science affords family goals. The finding that these perceptions decrease with age is important: as students move to life stages where their beliefs about family and career matter most for their own decisions, they are increasingly likely to see science as incompatible with family goals. Specifically, as students choose STEM electives in high school, courses in college, and career paths in college, achievement-related choices that are crucial to choosing a career in STEM (Wang and Degol 2013), they are simultaneously and increasingly perceiving incongruity between these career paths and their family goals.

Study 1 clearly demonstrated that those who perceive that science affords family goals are especially positive toward science. This finding suggests that perceptions about family goals might play a critical role in shaping decisions about entry into and persistence in science careers. However, Study 1 rests upon a correlational design, and thus it is always possible that third variables that were not measured could explain this relationship. In order to establish that perceptions that science affords family goals play a causal role in attraction to science careers, we turned to an experimental method in Study 2. In this study, we focus, in particular, on women's responses to framing STEM occupations as "family friendly," given that women may experience more work-family interference than men (Borelli et al. 2017; Duxbury et al. 1994).

3. Study 2

In Study 2, we examined whether experimentally manipulating the family-friendliness of an entry-level science career would elevate women's positivity toward science. In addition, in this study we expanded our positivity variables to include both general positivity toward science, as well as personal positivity toward pursuing science as a career. Although both attitudes are important in determining who persists in the STEM pipeline, personal favorability may be more challenging to influence with short-term exposure to information. However, understanding the beliefs that predict both general positivity and personal favorability are critical to forming interventions and policy to broaden participation in STEM.

In Study 2, we investigated two hypotheses. First, we hypothesized that framing a scientist's career as family-friendly will elicit greater general positivity toward science and personal positivity toward a career in science, particularly for women who are family-oriented. Second, we posited that this effect of family-friendly science will be mediated by beliefs that the scientist is fulfilled in life and in work. Thus, we expected that framing a scientist's career as family-friendly will lead to greater beliefs that the scientist is fulfilled, which will in turn predict positivity toward science and personal positivity toward pursuing science.

3.1. Methods

3.1.1. Participants

Participants included 87 women (M_{age} = 19.08), recruited from undergraduate psychology classes at a regional University in the Midwest. Students were predominantly European American (87%), with African American (7%), Hispanic American (2%), Asian American (2%), and Biracial (2%) students also represented in the sample. Students were predominantly first year students (74%), with smaller groups of second year students (17%), third year students (3%) and fourth year students (2%). Three non-traditional students were eliminated from analyses.

3.1.2. Procedures

Students were randomly assigned to one of two conditions, described below: (a) a family-friendly condition, and (b) a control condition in which family was not mentioned. After reading the description, students completed a brief measure of their positivity toward science, perceptions of people in science careers, and perceptions of career and life fulfilment.

3.1.3. Materials

A description of a day in the life of an entry-level female chemist was based on similar descriptions used by Diekman et al. (2011). The work-related tasks were the same across both conditions (e.g., "I go to the lab after about an hour to check on samples left overnight (for example, to see if a drug crystallized), characterize samples from the previous afternoon to integrate the data collected the previous day, and characterize new samples that have come in that day"). In the family-friendly condition, some events described interactions with spouse and children (e.g., "I wake up and wake the children. I watch morning cartoons with them for a bit."); in the control condition, these events described the same content but without spouse or children (e.g., "I wake up. I watch a bit of television in the morning.").

Both descriptions note that the scientist enjoys "working by myself and solving problems," and the work tasks are identical across the two conditions. Thus, unlike previous research (Diekman et al. 2011), the nature of the work is consistent across both conditions; instead, only the presence and support for family caregiving differs between the two conditions. See Appendix A for the complete descriptions.

Control Condition

In the control description, the chemist (Joyce) wakes up, watches television, gets dressed and makes lunch, walks to work, checks her email, and checks a research database to get up-to-date about some of her experiments. She then goes to her lab to check on samples left over night and prepare new samples and catches up on her research. She walks across campus for exercise.

Family-Friendly Condition

The description of the scientist was modified to include family responsibilities and caregiving. In this description, Joyce wakes up and wakes up her children, watches television with her children, gets herself dressed and the children dressed and makes them all lunch. She walks to work dropping the children off at day care along the way. While at work, the duties are identical to the duties in the control condition. Late morning, she walks across campus and visits her children as they have lunch.

3.1.4. Measures

Family Orientation

To capture individual differences in family orientation, participants responded yes or no to the question, "Have your future family plans factored into your career decisions?" Individuals responding "Yes" were categorized as high in family orientation and those responding "No" were categorized as low in family orientation.

Positivity toward Science

Two indices of positivity were assessed. First, an index of general positivity toward science was created by averaging two items (alpha = 0.73): "What is your general impression of an entry-level career in STEM?" and "What is your general impression of science careers?" with response options ranging from (1) Very Negative to (7) Very Positive. Second, an index of personal favorability toward pursuing a science career was created by averaging three items (alpha = 0.91): "How successful do you think you would be as an entry-level scientist?"; "How enjoyable do you believe you would find a career as an entry-level scientist?"; "How interested are you in a career as an entry-level scientist?" with response options ranging from (1) Not at all to (7) Extremely.

Fulfilment

Two items assessed fulfilment. The first item asked "How fulfilling do you believe the scientist you read about finds her career?" and the second item asked "How fulfilling do you believe the scientist you read about finds her life?" Response options for both questions ranged from (1) Not at All to (7) Extremely. These items were highly correlated (alpha = 0.76) and were averaged to create an index of perceived fulfilment.

Demographics

Participants reported demographic information, including gender, age, race, year in college, and current major.

3.2. Results

3.2.1. Positivity

We conducted a 2 (condition: family-friendly or control) × 2 (family orientation: high or low) multivariate analysis of variance (MANOVA) including both general positivity and personal favorability as dependent measures. This analysis yielded a significant interaction between condition and family orientation, $F(1, 85) = 3.23$, $p = 0.04$, *Wilk's* $\Lambda = 0.93$, *partial* $\eta 2 = 0.07$. Univariate analyses revealed that this interaction only emerged as significant for general positivity, $F(1, 85) = 6.53$, $p = 0.01$, *partial* $\eta 2 = 0.07$, and was not significant for personal favorability, $p = 0.17$. See Table 3 for means and standard deviations. To investigate this interaction, comparisons between conditions were examined for family-oriented and non-family-oriented women separately. Family-oriented women who read about a female scientist with a family were more positive toward STEM careers than family-oriented women who read about a female scientist without a family, $t(30) = 2.37$, $p < 0.02$, $d = 0.88$. There were no significant differences between conditions for non-family-oriented women. See Figure 2.

Table 3. Study 2: Means and Standard Deviations by Condition and Family Orientation.

	Family Friendly				Control			
	Family-Oriented (N = 13)		Non-Family-Oriented (N = 29)		Family-Oriented (N = 19)		Non-Family-Oriented (N = 28)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
General Positivity	5.85 [a]	0.94	5.13	0.82	4.82 [b]	1.36	5.29	1.01
Personal Favorability	4.08	1.16	3.41	1.42	3.21	1.84	3.51	1.59
Perceived Fulfilment	6.27	0.78	5.82	0.84	5.65	1.08	5.89	0.94

Note: Superscripts indicate significant differences across groups.

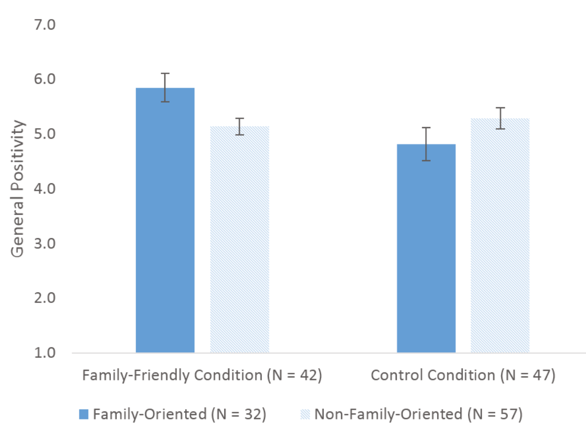

Figure 2. Positivity toward STEM careers by family orientation and condition.

3.2.2. Fulfilment

We examined effects on the perception that the scientist was fulfilled in a 2 (condition) × 2 (family orientation) ANOVA. There were no significant main effects of condition ($p = 0.19$) or family orientation

($p = 0.62$), and there was no significant interaction between the constructs ($p = 0.11$). See Table 3 for means and standard deviations.

3.2.3. Does Perceived Fulfilment Predict Positive Attitudes?

We had predicted that the family-friendly framing would foster positivity through perceptions that the scientist was fulfilled. Because we did not detect condition effects on perceived fulfillment, that mediational model was not supported. However, we were able to examine whether perceived fulfillment would be associated with positive attitudes toward pursuing science. We conducted a linear regression analysis to determine whether this projected sense of fulfilment predicted positivity toward science. For general positivity toward science, perceived fulfilment was a significant positive predictor, $B = 0.53$, $\beta = 0.47$, $p < 0.001$, and for personal favorability, perceived fulfilment was a marginal positive predictor, $B = 0.32$, $\beta = 0.19$, $p = 0.07$. On both measures, women who perceived that the scientist was more fulfilled tended to express more positivity toward science.

3.3. Discussion

In Study 2, we presented participants with a description of an academic science job that was framed as either typical (control) or family friendly. The female scientist in each of the scenarios performed typical duties of scientists, but the family friendly description contained information about spending time with her family members and caring for them, while the control description contained information about her hobbies and activities outside of work.

Our data indicate that family-oriented women who learn about a scientist whose work allows for the integration of caregiving responsibilities were more positive toward STEM than their peers. Thus, this research supports the goal congruity perspective as applied to the affordance and endorsement of family goals (Diekman et al. 2017; Weisgram and Diekman 2016). Specifically, the higher the congruity that was present between women's goals and their perception of STEM careers, the more positive they felt toward these careers in general. Based on this brief study, we may infer that intervention programs aimed at increasing girls' and women's positive evaluation of, STEM may benefit, at least for many individuals, from including information about work-life balance in STEM fields.

In addition to examining general positivity and personal favorability, we also examined the effect of framing STEM careers as family-friendly on the perceptions of personal fulfilment of the female scientist that was described. Although our framing of the STEM career did not affect perceptions of fulfilment, there were individual differences in the degree to which perceptions of fulfilment predicted STEM attitudes. We found that the sense that the scientist was perceived to be fulfilled, across both conditions, influenced attitudes toward STEM careers. For general impression of the field, this relationship was significantly positive: the more a participant perceived the scientist as fulfilled with her life, the more positive attitudes she had toward STEM careers in general. For personal favorability, perceptions that the scientist was fulfilled were positively (but marginally) related to positive STEM attitudes These patterns indicate that a sense that others are fulfilled in STEM careers is important in the development of positive STEM attitudes among women.

Across two studies, we demonstrate the potential impact of beliefs that science careers can be combined with family goals. Study 1 found that across developmental stages from middle school to college, both boys and girls are increasingly likely to perceive science as failing to afford family caregiving. Moreover, in early and late adolescence, these family affordances predict positivity toward STEM career paths. Thus, it is possible that perceiving STEM careers as not "family friendly" deters girls from exploring and pursuing STEM careers. Study 2 employed an experimental design to demonstrate that family-oriented individuals who read about a scientist who incorporates family roles expressed more general positivity toward a scientist career.

4. General Conclusions

Overall, these data suggest that highlighting the possibility of STEM careers as family-friendly might be a significant mechanism of intervention for broadening participation of family-oriented individuals—and perhaps more interventions should incorporate information about how STEM careers afford these goals. Interventions that incorporate other communal goals have been successful with adolescent girls and young women (Weisgram and Bigler 2006). Thus, interventions that include portrayals of scientists as multidimensional individuals who are both scientists and parents may increase girls' and women's positive attitudes and break down stereotypes about scientists. A strong caveat to this conclusion, however, is that such family-friendliness cannot only occur in marketing about careers; the real-life cultures of institutions and workplaces must encompass work-life resources (Weisgram and Diekman 2016).

To truly shift workplace cultures to encompass family goals, specific steps need to be taken to remove barriers that particularly influence women's entry and persistence in STEM. Indeed, Mason has widely implemented and discussed some of the ways in which STEM careers, and academic careers more broadly, can be made to help accommodate parents, such as stopping the tenure clock (Mason et al. 2013). In recent years, the National Science Foundation has begun to incorporate more family-friendly policies to help grant holders, including delaying the start of research due to pregnancy or parental leave (particularly for those for whom traveling with young children is dangerous or difficult) and providing additional funding for research assistants to carry out parts of the research that might be difficult or dangerous for a pregnant woman or parents with young children (e.g., paleontology digs in extreme heat, Arctic fieldwork, etc.). Some universities are even providing back-up child care services and sick child care in one's home at a partially subsidized rate to limit the impact child care disruptions have on faculty members' productivity—disruptions that disproportionally affect women (University of Michigan 2016).

Thus, although some steps are being taken to make STEM careers more family friendly, institutions and individuals still have a long way to go. A key message across intervention efforts should be to demonstrate that family goals and STEM careers are not in competition with one another, but can be integrated. In addition, qualitative and quantitative research should be conducted with female and male scientists that aims to investigate the complex challenges these individuals have in combining work with family, and to identify mechanisms that would enable them to be successful and fulfilled in both roles.

Despite the promising findings of these studies, there are a number of limitations to this research. Although the elegant design of Study 2 is useful in determining the causal role of family-friendly framing on individuals' STEM attitudes, it portrays scientists as either being isolated or having a family. Certainly, other forms of connection to people (besides child caregiving) can offer opportunities to meet communal goals. Future research using this vignette paradigm should also depict male and female scientists having a rich social network both in and outside of the workplace, having hobbies and outside interests, and having STEM jobs that afford a variety of values and goals. Given that family-orientation is ranked highly in women's occupational value structures (Weisgram and Hayes 2014) and that the construct moderates the effects of family-friendliness on positivity, we see value in emphasizing the ability to successfully integrate family and career roles in attracting women and girls to STEM fields.

An essential step for future research is to investigate how men navigate family and employment roles. Study 1 found that men and women held similar beliefs about whether science afforded family goals; as men become increasingly involved with caregiving and less able to assume a stay-at-home partner, they too may be faced with perceptions that work and family are incongruent. We anticipate that flexible work structures that allow both men and women to pursue their valued goals will be increasingly favored. However, an initial step is to understand whether both male and female scientists can model family-friendly STEM workplaces, and whether both male and female respondents weigh this information equivalently in their choices. In previous experimental studies, both male and female scientists conveyed opportunities to work with or help others within STEM roles (Fuesting and

Diekman 2017). However, because of the gendered nature of family caregiving, it is possible that female scientists can more effectively convey cues that STEM roles can integrate family.

In addition, future research should further examine the direction of the relationships assessed here through experimental and longitudinal research. The experimental method in Study 2 demonstrated that perceived family-friendliness can have a *causal* impact on positivity toward pursuing a science career. However, other naturalistic relationships are possible. For example, individuals who are highly immersed in science and positive toward the field may also have more opportunity to observe scientists who are involved in family caregiving or who are fulfilled in various ways. We also note that explorations of these constructs among individuals who vary in age, ethnicity, socioeconomic status, and a variety of other background variables would provide opportunity to understand the strengths and limitations of the framework explored here. In particular, it is important to understand whether groups vary in their perceptions that science affords family goals, and whether groups have differential access to resources to help them navigate perceived work-family conflict (e.g., affordable high-quality child care; extended family networks).

The experimental stimuli used here were designed to manipulate the presence or absence of family integration in academic science, and a question for extending this research is the ecological validity of this description. In short, does this vignette realistically depict a day in the life of a female scientist who is a primary caregiver or a co-parent? Many real-life situations are more challenging than depicted here: in the vignette, the scientist's children are healthy, they attend the same day care on her campus, have no afterschool activities, and she has a partner who participates in the daily division of labor. Although parents may experience many days such as the one described, daily life with young children can be decidedly more stressful (e.g., illnesses that prevent them from attending day care, the lack of availability of affordable high-quality child care for parents, the stresses that exist between co-parents of young children, and the difficulty of transitions as children develop; (Augustine et al. 2013; Hardway and McCartney 2015; Nelson et al. 2014)). However, these are issues that many families face regardless of discipline, and thus cannot explain gender gaps in STEM pursuits. Finally, we note that career decisions may often be based on ideals rather than reality; thus, the development of perceptions of scientists and science careers across age merits future research. What is important to note here is that when an idealized science career integrates family, it might be more appealing than when it does not.

The current research demonstrates that beliefs that family caregiving is incongruent with a science career become more extreme from adolescence through young adulthood, and this perceived incongruity can have strong implications for career decisions. For those who wish to create greater opportunity for women (and family-oriented men) in science, two paths are clear: First, scientists who do successfully integrate family can make these successes more public, and second, scientists who meet with challenges in integrating family can make these obstacles more public. When parents have to choose family or a scientific career, the losses accrue not only to those individuals, but to institutions, to science, and to society at large.

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Author Contributions: Erica S. Weisgram and Amanda B. Diekman both participated in designing the studies, analyzing data, and writing the manuscript. Erica S. Weisgram collected data for both studies.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Appendix A.1 Family Friendly STEM Condition

Joyce is a chemist at a university in the Midwest. She lives with her husband and two children (ages 1 and 3) in a home near the university. A sample day in her life is as follows:

6:30 a.m. I wake up and wake up the children. I watch morning cartoons with them for a bit. Then, I make breakfast and get dressed-helping the children get dressed as well. I pack lunches for them and for myself.

7:45 a.m. I walk to work, dropping off children at the University Child Care Center on the way.

8:15 a.m. I come in and check my e-mail then plan the day. I usually have to check a database maintained by the Operations Group (they run the high-throughput screens) to learn the status of ongoing experiments so I can go from primary to secondary characterizations.

9:15 a.m. I go to the lab after about an hour to check on samples left overnight (for example, to see if a drug crystallized), characterize samples from the previous afternoon to integrate the data collected the previous day, and characterize new samples that have come in that day. I look up relevant past research to consult about the procedures.

11:30 a.m. I often walk to the University Child Care Center to visit the children as they have lunch.

12:00 p.m. The company runs presentations during lunch, where we learn what else is going on both within the company and with the Big Pharma companies who supply us with compounds. I watch video feed of these presentations at my desk while I eat. Speakers might be a researcher from a different lab giving an update, a patent lawyer briefing us on legal issues in patent protection, and a member of the Products Group describing ongoing product development work.

1:00 p.m. Do data analysis (e.g., powder X-ray diffraction, differential scanning calorimetry, thermal gravimetric analysis) and troubleshoot any problems that come up by myself.

2:45 p.m. I call my spouse to check in and say hello and discuss what we should have for dinner that evening.

3:00 p.m. Go to meeting to update my supervisor on the status of my projects, which are typically independent. My supervisor will tell me what further experiments to run or additional data points to collect. My supervisor also gives me a heads-up on what compounds are coming in during the next few weeks. This gives me an idea of what my own workload will be like.

4:00 p.m. Update lab notebook with either data collected that day or experiments started. Get started on experiments that can be set up and run overnight.

4:30 p.m. Commute home.

5:30 p.m. I play with the children before starting dinner for my family. We have dinner, talk about our day, and my spouse cleans up afterwards.

6:30 p.m. We spend "family-time" together—often watching television, spending time in our yard, or going for a walk.

7:30 p.m. We put the children to bed.

8:30 p.m. I catch up on household chores such as laundry, dishes, and picking up items around the house.

9:15 p.m. I check my email from work and respond to any pressing issues and often complete a little bit of grading if needed.

10:00 p.m. I read a leisure book in bed for a bit to relax.

10:45 p.m. I get ready for bed and go to sleep.

Summary I like that so much of my work involves working by myself and solving problems. The solitary nature of my work really lets me advance at a quick pace, and I get the sense that I am achieving a great deal through my projects. I like having a variety of tasks, gathering data through multiple methods, and trying to interpret data from both high-throughput experiments and bench-top experiments. I like the sense of contributing to understanding drug candidates that are likely to get into clinical trials. I like being exposed to industry and to the various issues in the pharmaceutical industry, both within my field and outside—largely from presentations—from the senior scientists and other experts. I also like that I have a flexible schedule that allows me to spend time with my family.

Appendix A.2 Control Condition

Joyce is a chemist at a university in the Midwest. She lives in a home near the university. A sample day in her life is as follows:

6:30 a.m. I wake up. I watch a bit of television in the morning. Then, I make breakfast and get dressed. I pack a lunch for myself.

7:45 a.m. I walk to work.

8:15 a.m. I come in and check my e-mail then plan the day. I usually have to check a database maintained by the Operations Group (they run the high-throughput screens) to learn the status of ongoing experiments so I can go from primary to secondary characterizations.

9:15 a.m. I go to the lab after about an hour to check on samples left overnight (for example, to see if a drug crystallized), characterize samples from the previous afternoon to integrate the data collected the previous day, and characterize new samples that have come in that day. I look up relevant past research to consult about the procedures.

11:30 a.m. I often walk across campus for exercise.

12:00 p.m. The company runs presentations during lunch, where we learn what else is going on both within the company and with the Big Pharma companies who supply us with compounds. I watch video feed of these presentations at my desk while I eat. Speakers might be a researcher from a different lab giving an update, a patent lawyer briefing us on legal issues in patent protection, and a member of the Products Group describing ongoing product development work.

1:00 p.m. Do data analysis (e.g., powder X-ray diffraction, differential scanning calorimetry, thermal gravimetric analysis) and troubleshoot any problems that come up by myself.

2:45 p.m. I decide what to have for dinner that evening and make a shopping list.

3:00 p.m. Go to meeting to update my supervisor on the status of my projects, which are typically independent. My supervisor will tell me what further experiments to run or additional data points to collect. My supervisor also gives me a heads-up on what compounds are coming in during the next few weeks. This gives me an idea of what my own workload will be like.

4:00 p.m. Update lab notebook with either data collected that day or experiments started. Get started on experiments that can be set up and run overnight.

4:30 p.m. Commute home.

5:30 p.m. I make dinner and clean up afterwards.

6:30 p.m. I often watch television, spend time in my yard, or go for a walk.

7:30 p.m. I spend time working on my hobbies

8:30 p.m. I catch up on household chores such as laundry, dishes, and picking up items around the house.

9:15 p.m. I check my email from work and respond to any pressing issues and often complete a little bit of grading if needed.

10:00 p.m. I read a leisure book in bed for a bit to relax.

10:45 p.m. I get ready for bed and go to sleep.

Summary I like that so much of my work involves working by myself and solving problems. The solitary nature of my work really lets me advance at a quick pace, and I get the sense that I am achieving a great deal through my projects. I like having a variety of tasks, gathering data through multiple methods, and trying to interpret data from both high-throughput experiments and bench-top experiments. I like the sense of contributing to understanding drug candidates that are likely to get into clinical trials. I like being exposed to industry and to the various issues in the pharmaceutical industry, both within my field and outside—largely from presentations—from the senior scientists and other experts.

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Entry and Degree Attainment in STEM: The Intersection of Gender and Race/Ethnicity

Yingyi Ma * and Yan Liu

Department of Sociology, Syracuse University, Syracuse, NY 13244, USA; yliu43@syr.edu
* Correspondence: yma03@syr.edu

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Abstract: This study focused on entry to and attainment of bachelor's degrees in science, technology, engineering, and mathematics (STEM) fields, by examining gender and race/ethnicity in an intersectional manner and paying particular attention to STEM subfields. The intersectional analysis extends previous research findings that female students are more likely to persist in college once they are in a STEM field and further reveals that racial minority women share the same tendency of persistence with white women. Women and racial minorities are most under-represented in physical-STEM fields. Our analysis reveals that black men would have had the highest probability to graduate in physical-STEM fields, had they had the family socioeconomic background and academic preparations of Asian males. This highlights the critical importance of family socioeconomic background and academic preparations, which improves the odds for STEM degree attainment for all groups. Out of these groups, black students would have experienced the most drastic progress.

Keywords: gender; race; STEM; persistence; intersection

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1. Introduction

The recent release of *Science and Engineering Indicators* (2016) once again highlights the under-representation of women and non-Asian racial minorities in science, technology, engineering, and mathematics (STEM) degree attainment, and in the STEM labor force (National Science Board 2016). This is a significant social issue, as STEM fields witness more job growth and promise higher earning potential than non-STEM fields. So, the under-representation of women and racial minorities in STEM could increase labor market inequality along race and gender lines. On a different level, as the demographics of the American population become more diverse, STEM workforce needs to catch up with demographic changes. Otherwise, the country runs the risk of losing its competitive advantages in the world.

The under-representation of women and racial minorities in STEM is particularly acute now, as racial minorities have made significant inroads into postsecondary institutions, and women in recent years have been obtaining bachelor's degrees at a higher rate than men (Buchmann and DiPrete 2006). However, the increase of access to colleges and universities does not automatically bring about an increase of enrollment in STEM fields. Therefore, it is an increasingly worthy task for researchers to understand the processes leading to the under-representation of women and racial minorities in STEM fields.

Recent research has brought additional complexity to the theme of under-representation. Studies have shown that black students are as likely as their white counterparts to claim college majors in STEM fields (Hanson 2009; Ma 2009; Riegle-Crumb and King 2010). That is, initially, they are not under-represented in STEM fields; however, they are eventually under-represented in STEM degree attainment, but it is not clear why. Racial disparity in degree attainments generally exists, but we are not sure whether STEM degree attainment poses additional barriers for racial minorities. Research is needed to disentangle the process of STEM degree attainment from general degree attainment.

In addition, this study also pays particular attention to STEM subfield variations, as women and racial minorities are not uniformly under-represented across STEM subfields. Previous studies have documented strongly that women and racial minorities have made great inroads into life science and related STEM fields, but they are persistently under-represented in such fields as physics, computer science, and engineering (England and Li 2006; Frehill 1997; Ma 2009; Sassler et al. 2017). In computer science, women's representation has surprisingly declined by 2013, as compared to the 1980s (Corbett and Hill 2015; Sassler et al. 2017). Engineering has witnessed more growth, but it still remains heavily male-dominated (Xie et al.). For this reason, this study has differentiated STEM into life-STEM and physical-STEM fields, with the former including agricultural, biology, and other life science-related STEM fields, and the latter including physical science, math, computer science, and engineering.

This study focuses on both entry-level majors and bachelor's degree attainment in STEM fields—the admission ticket to many STEM occupations (Xie and Shauman 2003). It examines patterns of representation in STEM subfields for the intersection of gender and racial/ethnic groups. It uses the *National Education Longitudinal Studies* (1988:2000) (NELS) from the National Center for Education Statistics. The NELS data make possible an examination of the process from college entry to degree completion, and also enable an examination of racial minorities, as the survey over-sampled Asians and Hispanics. The data also contains rich contextual information on high school academic preparations, which are important to understand STEM attainment in college.

In what follows, I will first review theoretical and empirical studies using intersectional perspectives of gender and race, and then review the relevant literature in understanding the process of STEM degree attainment. The process of STEM degree attainment can be understood from two angles. One is the trajectory that students have traveled. Do students graduate with STEM degrees by choosing their initial college majors in STEM and then persisting, or do they start with a non-STEM major and then switch later to STEM? The second angle is to understand the extent to which key background factors including family socioeconomic status and academic preparations account for group disparity in STEM attainment. The intersectional perspectives of race and gender can help elucidate new patterns and insights about the process of STEM degree attainment, in terms of both trajectories and contextual explanations for group disparity.

2. Intersectionality Studies

Critical race theorist and legal scholar Kimberlé Williams Crenshaw coined the term "intersectionality" in 1989 to address the marginalization that African American women and other women of color faced in both feminist and antiracist politics and theory. Crenshaw argued that the experience of women of color cannot be understood in terms of their gender or race. Therefore, she used the concept to denote the many ways in which race and gender interact to influence the experiences of African American women. In her book titled "Ain't I A Woman? Black women and feminism," scholar and social activist bell hooks examines the history of sexism and racism on black women and the civil rights movement and waves of feminist movements to the 1970s, against both forms of oppressions, which together have caused black women to suffer the most in American society (hooks 1981). While the idea of intersectionality was developed largely based on the experience of women of color, the concept has expanded to refer to the insight that social locations such as race, ethnicity, gender, class, sexuality, nationality, ability, and age do not function as stand-alone and mutually exclusive entities (Collins 2015, p. 2). In this sense, intersectionality calls attention to power relations that create social inequalities and injustices (Collins 2015, p. 5). Power shapes privileged and oppressed social categories that are interconnected, creating a "matrix of domination" (Collins 2015).

However, in understanding educational experiences in STEM fields, most studies treat gender and racial minorities in the aggregate, as if all men and women share similar experiences in STEM fields. It is also problematic to presume that gender is irrelevant when we examine racial/ethnic disparities in STEM fields (Muller et al. 2001). Recent research on subgroups clearly underscores the significance of examining gender and race/ethnicity from an intersectional perspective. Hanson (2009) found that African American girls, contrary to the expectation that they are doubly disadvantaged in STEM fields as members of two under-represented status groups, show a greater interest and a more positive attitude towards science than their white counterparts. A study by Riegle-Crumb and King (2010) questions the assumption that STEM fields are still dominated by white males, and they find that racial minorities are not under-represented as compared to whites in entering STEM fields in terms of college major choices. Unfortunately, their study has not included Asian students, a group highly visible in STEM. Also, their study examines only college major choices two years after high school. Their conclusion, consequently, cannot apply to ultimate degree attainment, in which racial minorities still fall behind.

Most recently, Ro and Loya (2015) have found out that among a sample of engineering students, black women rate their skills lower than white men and women, and also lower than black men. The authors suggest that black women may be suffering "a double effect because of their gender and race" (Ro and Loya 2015, p. 385). On the other hand, Ma (2010) has found that Asian women hold quite a positive attitude towards STEM fields, much more than their white counterparts. Lord et al. (2009) argue that many studies on engineering education literature fails to disaggregate women by race/ethnicity, therefore getting overgeneralized results that render minority women invisible. The intersectional analysis is needed to fully understand the group disparity in STEM attainment.

3. Pipeline Model or Revolving Door?

The "pipeline model" has been widely-used to understand the process of choice and attainment in STEM (Berryman 1983; Xie and Shauman 2003). As the metaphor of the pipeline indicates, the process is characterized by uni-directional rigid steps in choosing a college major and then persistence in attaining the degree. Other educational trajectories, e.g., choosing a non-STEM major initially, are viewed as "leaking from the pipeline." The pipeline imagery is grounded in the framework of cumulative disadvantage theory (Merton 1968; DiPrete and Eirich 2006), which posits higher attrition rates among traditionally under-represented groups, such as women and racial minorities. The theory then holds that the probability of a later influx into the pipeline is small, and therefore, complete persistence should be the dominant means for any group to attain a STEM degree.

Contrary to cumulative disadvantage theory and the pipeline model, the revolving door theory—proposed by Jerry Jacobs (1989) in his seminal study of occupational sex segregation—provides a different approach that enables a more dynamic and fluid perspective. Jacobs found substantial flows of women into and out of male-dominated occupations. The "revolving door" perspective captures fluidity in aspirations and choices, allowing for delayed entry and attainment. Recent studies provide some empirical evidence for this view (Xie and Shauman 2003; Ma 2011), which indicates that most female STEM baccalaureates enter the STEM educational trajectory during college, after entertaining high school expectations of a non-STEM college major, whereas most male STEM baccalaureates anticipated majoring in a STEM field and held to this course in college. Ma (2011) further argued that the social control that prevents women from entering math and science fields during their pre-college years may ease up in college, which may help account for the influx of women into STEM later, in college. However, we are not yet certain of the more complex picture that may emerge after an examination of the intersection of gender and race/ethnic groups. Will racial minority women follow a similar trajectory of STEM degree attainment as white women, due to the more open and supportive environment in college than pre-college years? The intersectional analysis will provide empirical evidence to address this question.

4. Social Background Effects on STEM Choice and Attainment

Research has provided robust evidence for the impact of such contextual factors as family factors—particularly family SES—and high school academic preparations on STEM choice and attainment. There are substantial differences in STEM coursework and achievement between low-SES and high-SES students spanning from elementary schools to college (Miller and Kimmel 2012; NSB 2014). Various studies posit that high-SES parents can provide the necessary resources, exposure, and access to experiences that lead to later interest and participation in STEM (Archer et al. 2012; Dabney et al. 2013; Sjaastad 2012). In this aspect, racial minorities, black and Hispanic students in particular, are disadvantaged because they disproportionately derive from low-income households. Under-represented racial minorities are more likely to be in remedial courses and less likely to take advanced math and science courses than their white and Asian peers (Kelly 2009; Nord et al. 2011; NSB 2014). It is important to disentangle the effects of race from those of family SES, although they highly correlate in the U.S.

Academic preparations in pre-college math and science have been identified as the key determinants for participation in STEM fields in college (Adelman (1998, 2006); Smyth and McArdle 2004; Tai et al. 2006). However, recent research has consistently documented that aggregate gender differences in academic preparation, such as course taking and test scores, are negligibly small and can account for virtually nothing of the differences in the choice of a STEM major (Simon and Farkas 2008; Xie and Shauman 2003). Performance at the college level also influences students' educational trajectory, leading to STEM degree attainment. Some research suggests that when women and minorities fail a course, they are more likely not to repeat the course and to switch their major (Seymour and Hewitt 1997). Course grades in the first years of college may predict program retention (May and Chubin 2003). Few studies at the national level exist concerning the intersection of gender and race/ethnic patterns. However, some studies have shown that African American females have higher levels of academic preparation than their male counterparts (Hyde and Linn 2006; Riegle-Crumb 2006), and Asian American women show a much stronger tendency than white women to major in STEM fields, though they still fall behind Asian men (Ma 2011).

5. Research Questions

This study investigates the following questions:

- What are the patterns of representation in STEM fields in college in terms of the intersection of gender and racial/ethnic groups?
- How does the group representation vary at the starting and end points of students' college careers? Is under-representation among minorities driven mainly by their lower overall likelihood of finishing college, or does persisting in a STEM field pose additional barriers?
- How do race and gender distributions vary across STEM fields? Specifically, we distinguish life-STEM (biology and life sciences) and physical-STEM (physical science, math, computer, and engineering). How do race and gender distributions vary across STEM fields after taking into account family and academic backgrounds?

6. Data and Analytical Samples

The study uses the NELS: 88-2000 and the Postsecondary Education Transcript Study, which is the nationally representative dataset, collected by the National Center of Survey Statistics (NCES). NELS data is the most recent nationally representative longitudinal study that spans from students' 8th grades to 8 years after high school. The 1988 eighth grade cohort was followed at two-year intervals as the students passed through high school and entered post-secondary education. Similar to previous datasets collected by NCES, NELS data contain rich information on student pre-college academic preparation, including detailed information on coursework, and its postsecondary transcript data contains detailed curriculum and postsecondary attendance and attainment information. This survey allows for study of college access, college major choice, and degree attainment. The studies also oversampled Asians and Hispanics, which makes it possible to study racial patterns as well.

Since this study examines two sequential outcomes—the initial college major choice and STEM degree attainment—there are two distinct samples. For the initial major choice, the sample consists of all the postsecondary participants, based on transcript data, who also identify as one of four racial/ethnic groups: non-Hispanic Whites, non-Hispanic Blacks, Hispanics, and Asians. This results in 9272 students—among whom, 1657 has claimed STEM fields as their initial major, 5555 has claimed non-STEM fields as their initial majors, and 2060 students were undecided. The sample for STEM degree attainment consists of all those with bachelor's degrees, and the sample size is 4020—among whom, 1013 have attained STEM degrees. Appropriate weights variables are also employed in the analysis.

7. Variables

7.1. Dependent Variables

The dependent variables are the initial college major, and bachelor's degree major. The NELS data have the first college major information; bachelor's degree major information was obtained from the NELS: 88/2000 Postsecondary Transcript files. An aggregated variable with 12 categories (BAMJR) is used, and STEM fields include life science, math, physical, and computer sciences, engineering (of all sorts); the rest are non-STEM fields. STEM fields are further differentiated into life-STEM (agriculture, biology, and life-science related), and physical-STEM (computer, math, physical science, and engineering). This coding is a modified version of the coding used by the National Science Foundation, as well as by other researchers (Frehill 1997; Ma 2011).

7.2. Independent Variables

7.2.1. Academic Preparation

Academic preparation is measured using high school course taking and standardized test scores in math and science from the 12th grade and first year college GPA. These factors are domain-specific, and are considered to be important factors for the bachelor's degree attainment in STEM fields. Course taking information was gathered from high school transcripts, and includes the highest math course taken in high school. It has nine categories: Basic/Remedial Math, General/Applied Math, Pre-Algebra, Algebra I, Geometry, Algebra II, Advanced Math (Algebra III, Finite Math, Statistics), Pre-calculus (including Trigonometry), and Calculus. The course taking and test scores have some missing, and we use group means to impute for those missing values.

7.2.2. Demographic Variables

Demographic variables include gender, race, and family socioeconomic status (SES). Race consists of four categories: non-Hispanic Whites, non-Hispanic Blacks, Hispanics, and Asian/Pacific Islanders. Family SES is a composite measure drawn from information on both parents' education and their occupations and income.

8. Findings

8.1. Entry

Figure 1 presents the percentage of students from eight groups who chose a STEM field as their first college major. Because most of the participants were in their second year in college, a bit more than one fifth of students had not yet declared a college major. Asian males topped the chart, with more than 30 percent in STEM. The lowest male group—Hispanics—had more than 20 percent in STEM fields, still higher than the highest female group—Asian females, at 19 percent. While males are overall more likely to enter STEM fields than females, there are significant group variations across STEM subfields. In general, life-STEM fields witnessed much more female presence, while physical-STEM fields had a quite low female presence. In particular, over 12 percent of Asian females entered life-STEM fields, surpassing all male groups. The other notable finding was that blacks were not at all under-represented. Black males were as likely as white males to claim STEM majors. Black females are more likely than white females to enter STEM fields. More than 14 percent of black females had their first college major in a STEM field, compared to less than 11 percent of white females. In particular, black females are about twice as likely as their white counterparts to enter physical-STEM fields. Black females also overtook Asian females in their entry to physical-STEM fields.

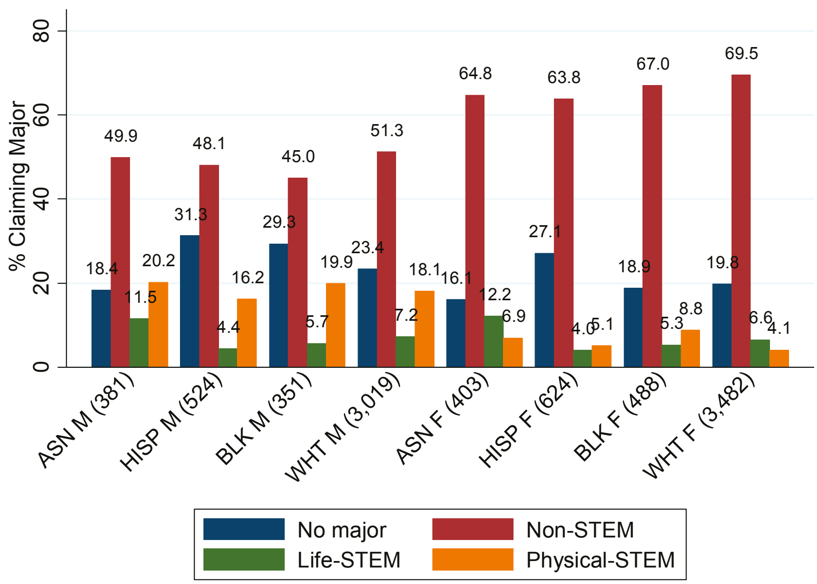

Figure 1. Gender and Race Disparity in Entry into science, technology, engineering, and mathematics (STEM) fields (N = 9272). Note: Data is from *National Education Longitudinal Studies* (NELS:88-00) postsecondary transcript data. The sample consists of all the postsecondary participants, based on transcript data, who also identify as one of the four racial/ethnic groups: non-Hispanic Whites, non-Hispanic Blacks, Hispanics, and Asians. The parenthesis includes the sample size for each group.

8.2. STEM Degree Attainment

Figure 2 shows the group patterns in STEM bachelor's degree attainment. The NELS data collected entry information (initial college major choices) in 1994, and the degree attainment information in 2000, eight years after high school. Figure 2 shows that among the 9272 students who were enrolled in college in 1994, a significant number of them have no degrees six year later. Racial gaps are paramount. Over 65 percent of black males and 64 percent of Hispanic males have not obtained any degrees, compared with 33 percent of Asian females with no degrees—the lowest among all the groups. In terms of STEM degree attainment, Asian females have a higher rate of STEM degree attainment than all of the male groups, except for Asian males. Close to 20 percent of the Asian females have attained bachelor's degrees in STEM fields, compared to less than 15 percent of white males and less than 10 percent of black and Hispanic males. Asian males still topped the chart, with 24 percent graduating in STEM. There are significant variations across STEM-subfields. In particular, Asian females have the highest representation in life-STEM fields among all race-gender groups, with over 14 percent of Asian females graduating from life-STEM fields. However, less than 6 percent of Asian females graduated from physical-STEM fields and they trailed behind every male group, except for Hispanic males. Physical-STEM fields seem to be daunting for all females, with Asian females most represented (less than 6 percent) among all females. Although black females surpassed Asian females in their tendency to choose a physical-STEM major, they were left behind when it comes to degree attainment.

Given both black males and females were initially not under-represented in STEM fields but eventually are, this suggests a severe attrition issue for black students. But the question remains: Are the seemingly high attrition rates due to their higher rate of dropping out of college, or due to their higher rate of switching out of STEM fields?

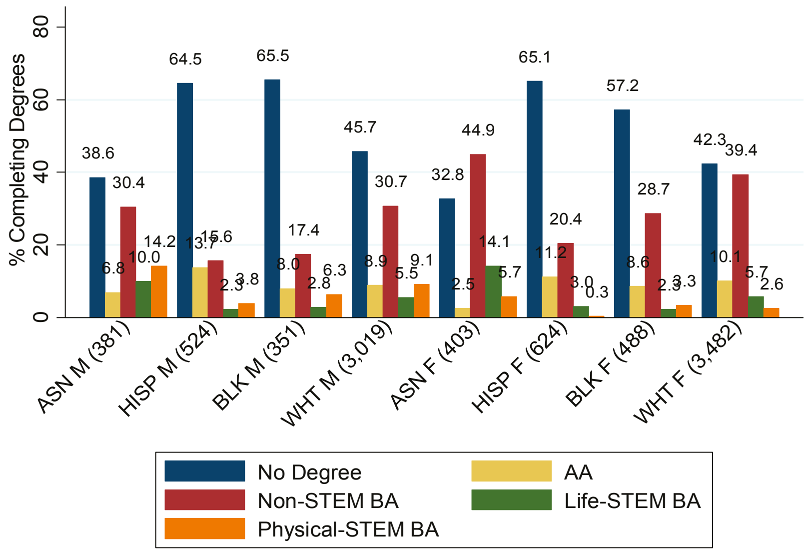

Figure 2. Gender and Race Disparity in Completing a STEM bachelor's Degree (*N* = 9272). Note: Data is from NELS: 88-00 postsecondary transcript data. The sample consists of all the postsecondary participants, based on transcript data, who also identify as one of the four racial/ethnic groups: non-Hispanic Whites, non-Hispanic Blacks, Hispanics, and Asians. The parenthesis includes the sample size for each group.

8.3. Attrition for Those with Initial Majors in STEM and Non-STEM Fields

Figures 3 and 4 can help address the above questions. Figure 3 examines outcomes for those who claimed a STEM field as their initial college major. There were 1657 students who had initial majors in STEM in 1994. These students could have four potential outcomes in 2000: no degree, associate degree, bachelor's degree in STEM fields, and bachelor's degree in non-STEM fields. A strong pattern emerges: females of all groups persisted slightly more than males, and Asian females had the highest persistence rate among all of the groups. Among those who claimed a STEM field as their initial college major, 62 percent of Asian females ultimately attained their bachelor's degree in a STEM field, followed by 56 percent of Asian males and 46 percent of white females. Among STEM graduates, all the males have more degrees in physical-STEM than in life-STEM, and the reverse is true for females, but black females remain the exception. While black females and white females share similar percentage in physical-STEM fields (over 15 percent), there are 13 percent of black females in life-STEM fields, compared with over 30 percent of white females in life-STEM fields.

A close examination of the question of attrition shows that black males have the highest percentage of dropping out of college: over 57 percent of those who initially claimed a STEM college major left college without any degree, compared to less than 20 percent of Asian females. Hispanic males were equally likely to drop out of college. Since there were many fewer black and Hispanic students completing college, the number of those who switched out of STEM and graduated with a non-STEM degree was also less than the number of white and Asian students.

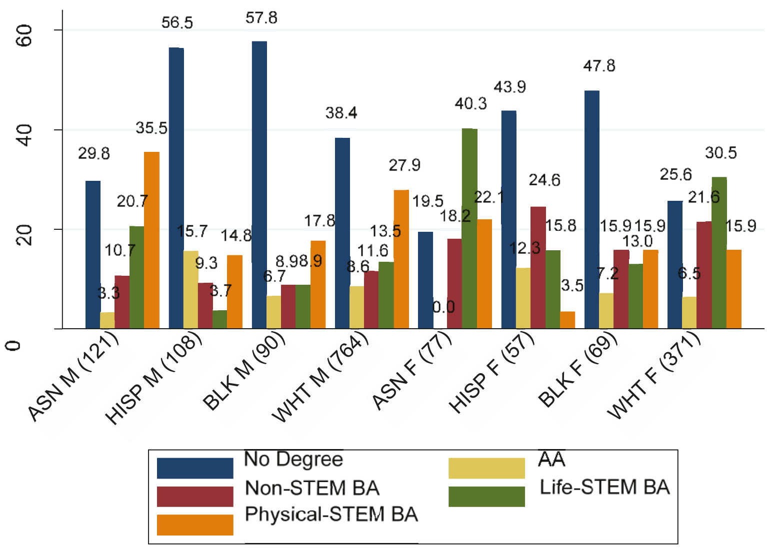

Figure 3. Gender and Race Disparities in the Outcomes among those with an initial STEM major. (N = 1657). Note: Data is from NELS:88-00 postsecondary transcript data. The sample size includes all with the initial college major in STEM fields. The parenthesis includes the sample size for each group.

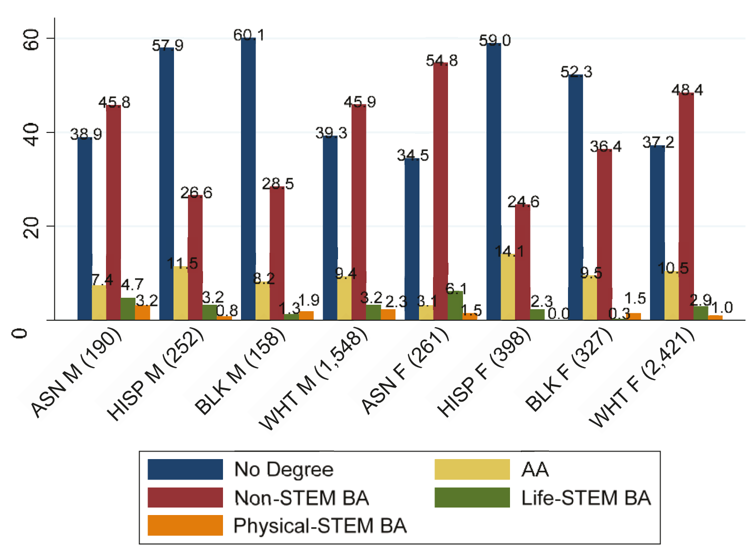

Figure 4. Gender and Race Disparities in the Outcomes among those with an initial non-STEM major. (N = 5555). Note: Data is from NELS:88-00 postsecondary transcript data. The sample size includes all with an initial major in non-STEM fields. The parenthesis includes the sample size for each group.

Figure 4 examines the outcomes of those with an initial major in a non-STEM field. This figure, along with Figure 3, offers a comparison of the attrition rates among those who started with STEM and non-STEM fields. The interesting pattern emerges that for females, entering a STEM field is associated with a much lower attrition rate than entering a non-STEM field; this pattern is not so strong for males. For example, more than 34 percent of Asian females in non-STEM fields dropped out of college, compared to less than 20 percent of their counterparts in STEM fields; close to 60 percent of Hispanic females in non-STEM fields left college with no degree, compared to 44 percent of their counterparts in STEM fields. The same pattern applies to white females: 37 percent in non-STEM fields did not complete college, compared to only 25 percent of their counterparts in STEM fields. Black females exhibit similar patterns, though the gap is not as salient. This seems to indicate that female students who enter STEM fields are positively selected in ways that drive them to persist in college.

For males, entry into STEM does not make as much of a difference in completing college, with the exception of Asian males. Less than 30 percent of Asian males in STEM fields drop out of college, compared to 39 percent of their counterparts in non-STEM fields. Blacks show a similar pattern, but the gap is not salient. For whites and Hispanics, the type of college major makes virtually no difference.

8.4. Trajectory of STEM Degree Attainment

Figure 5 examines the pathways of STEM degree attainment. Among 1013 students who finally attained STEM degrees in 2000, 679 students (67 percent) claimed their initial college majors in STEM, in other words, they followed the pathway of early entry and persistence; about 334 students entered STEM later in college, after initially not in STEM. Apparently, the early entry and persistence pathway is a dominant one. But the intersection of race and gender group analysis reveals the importance of non-dominant path. Figure 5 shows that Asian women, Hispanic women and white women are all more likely to travel the non-dominant pathway than their male counterparts. The only exception is black women, with a quarter of them attaining STEM degrees after initially in a non-STEM field, compared to 40 percent of Asian and white women and 47 percent of Hispanic women who did so.

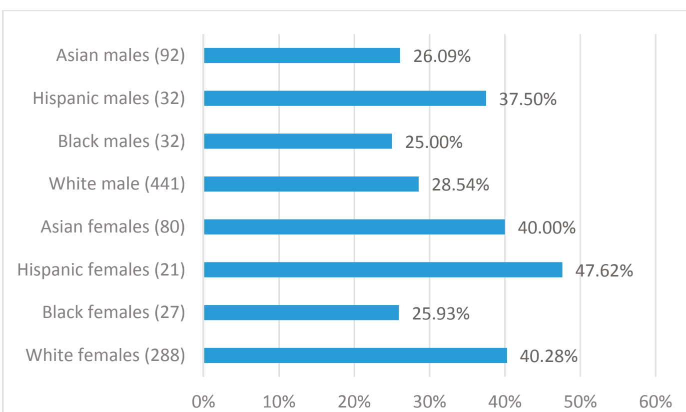

Figure 5. Gender and Race Disparities in Traveling the Non-Dominant Path of STEM Degree Attainment (N = 1,013). Note: Data is from NELS:88-00 postsecondary transcript data. The sample size includes all with the STEM bachelor's degrees by 2000. The parenthesis includes the sample size for each group.

Table 1 shows group disparities in key variables in family and academic backgrounds. For the highest math course taken during high school, contrary to the conventional wisdom that females trail behind males, both Asian females and black females surpassed their male counterparts. Meanwhile, whites and Hispanics maintained the traditional gender gap in favor of males. Asian females went the furthest in terms of the highest math course taken. Racial gaps are salient, in that blacks and Hispanics trail behind whites and Asians. Similar racial gaps manifest for standardized math achievement test scores. However, the female advantage in math course taking starts to trail off in standardized test scores, with both Asian and black females coming close to their male counterparts.

Table 1. Gender and Race Disparities in Key Independent Variables.

	SES (from −2.43–2.54)		**Highest Math (from 1–6)**		**Math Score (from 30.27–71.37)**		**College GPA (from 0–4)**	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Asian Male	0.27	0.88	4.18	1.57	57.24	8.41	2.68	0.77
Hispanic Male	–0.35	0.78	2.91	1.40	49.79	8.13	2.43	0.70
Black Male	–0.15	0.80	2.91	1.19	46.66	7.66	2.24	0.71
White Male	0.30	0.70	3.58	1.45	55.59	8.02	2.59	0.74
Asian Female	0.30	0.90	4.33	1.48	56.92	8.17	2.82	0.72
Hispanic Female	–0.46	0.76	2.82	1.22	47.85	7.45	2.48	0.75
Black Female	–0.26	0.77	3.14	1.26	47.14	7.87	2.41	0.72
White Female	0.20	0.71	3.41	1.40	53.76	7.75	2.76	0.72
Full sample	0.13	0.79	3.44	1.44	53.40	8.46	2.63	0.74

Note: Data is from NELS:88-00 postsecondary transcript data.

8.5. Predicted Probabilities of Majoring in STEM Subfields

Figures 6 and 7 present the predicted probability based on the logistic regression model of entry into life-STEM majors and physical-STEM majors. The model includes the key independent variables in academic preparation and family SES (their details are in Table 1). The blue bars represent predicted probabilities for each of the race and gender groups with the academic and SES variables set at the group-specific mean. Given that Asian males have the highest STEM degree attainment, the orange bars represent predicted probabilities for each of the race and gender groups, with the academic and SES variables set at the mean for Asian men. The comparison between the two sets of bars can elucidate how much of the group gaps can be closed by equalizing family background and academic preparations. Figure 6 shows that all the groups have increased their predicted probabilities in entry to life-STEM fields if they have had the same group mean in academic and family backgrounds with Asian men, except for Asian women. It is no surprise that Table 1 already shows Asian women have more academic advantages than Asian men. However, these academic advantages do not translate to much presence in physical-STEM fields. As Figure 7 shows that Asian women are much less represented in physical-STEM fields than other male groups, and also than black women. After setting group means at the level of Asian men's, the predicted probability for black women in entering physical-STEM fields is 0.122, compared with 0.06 of Asian women. The biggest change took place for black men. The predicted probability of black men in entering physical-STEM fields jumped to 0.285, had they had the family and academic backgrounds of Asian men. Figure 7 also shows that black men thus have the highest propensity to enter physical-STEM fields, had they had the family and academic backgrounds of Asian men.

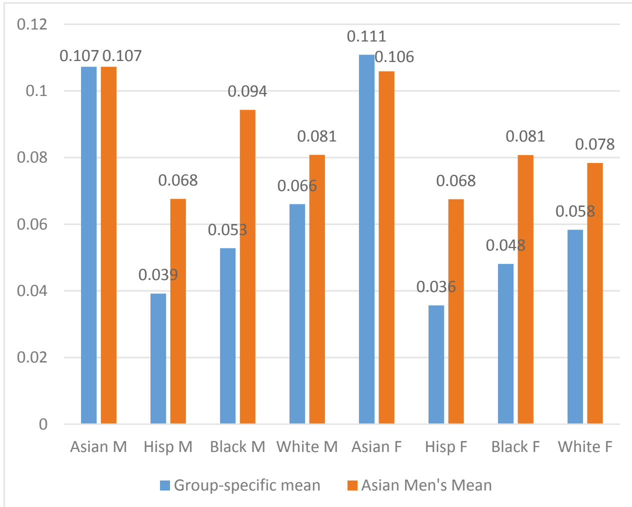

Figure 6. Predicted Probability of Choosing a Life-STEM Major for Race and Gender Groups. Note: Data is from NELS:88-00 postsecondary transcript data. Blue bars represent the predicted probability when independent variables (i.e., family SES and academic preparations) are set at the group-specific mean; Orange bars represent the predicted probability when independent variables are set at the mean of Asian men).

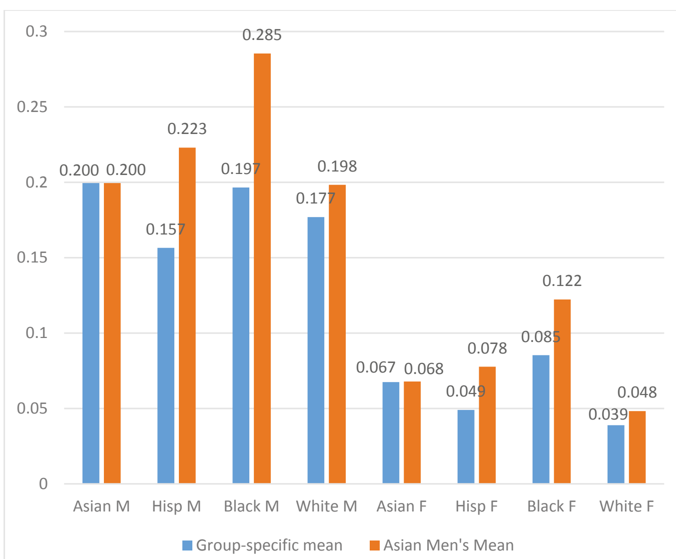

Figure 7. Predicted Probability of Choosing a Physical-STEM Major for Race and Gender Groups. Note: Data is from NELS:88-00 postsecondary transcript data. Blue bars represent the predicted probability when independent variables (i.e. family SES and academic preparations) are set at the group-specific mean; Orange bars represent the predicted probability when independent variables are set at the mean of Asian men).

8.6. Predicted Probabilities of Degree Attainment in STEM-Subfields

Figures 8 and 9 present the predicted probabilities based on the logistical regression of STEM degree attainment for life-STEM and physical-STEM fields respectively. Similar methods were used as in Figures 6 and 7 to compare the predicted probabilities before and after setting the mean at the level of Asian men, in terms of family and academic background variables. Figure 8 has shown that salient changes took place for both black males and Hispanic females. The predicted probability has jumped to 0.077 from 0.02 for black males to graduate in life-STEM fields after taking on the mean of Asian male's academic and family background. The increase for Hispanic females from 0.018 to 0.072 is also quite remarkable. Figure 9 focuses on physical-STEM fields. It has shown the most striking changes for black males. The predicted probability for black males to graduate in physical-STEM has jumped to 0.186 from its previous 0.031, had they had the family and academic attributes of Asian males. Notably, the predicted probability of Asian males to graduate in physic-STEM fields is 0.096, only half of the level of black males with Asian characteristics.

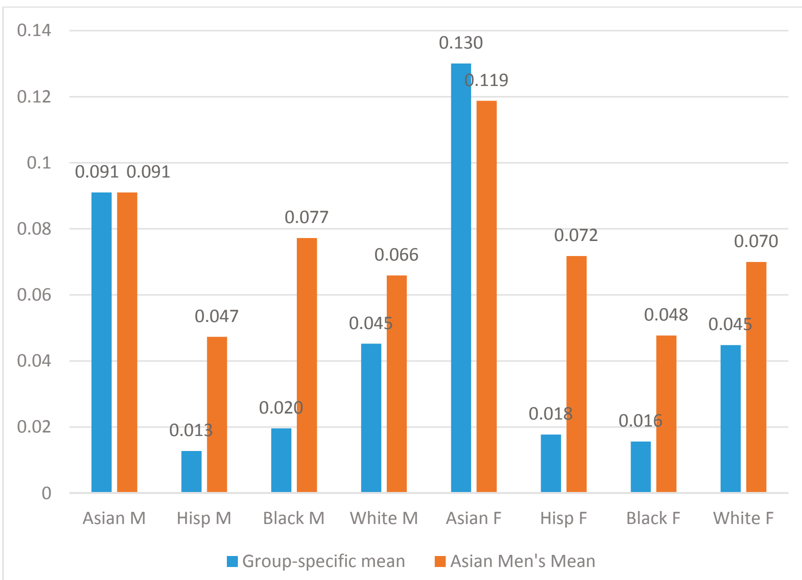

Figure 8. Predicted Probability of Attaining a Life-STEM Bachelor's Degree for Race and Gender Groups. Note: Data is from NELS:88-00 postsecondary transcript data. Blue bars represent the predicted probability when independent variables (i.e. family SES and academic preparations) are set at the group-specific mean; Orange bars represent the predicted probability when independent variables are set at the mean of Asian men).

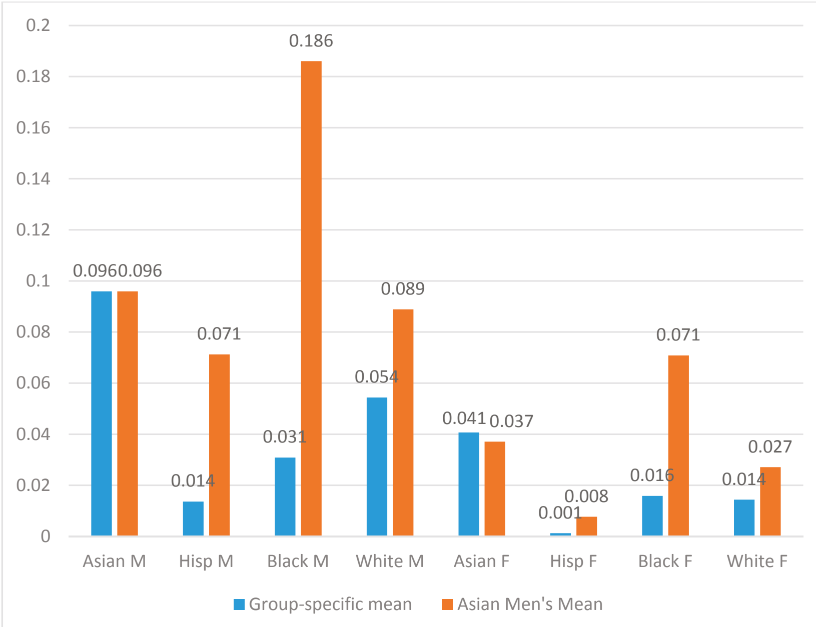

Figure 9. Predicted Probability of Attaining a Physical-STEM Bachelor's Degree for Race and Gender Groups. Note: Data is from NELS:88-00 postsecondary transcript data. Blue bars represent the predicted probability set at group-specific mean; Orange bars represent the predicted probability set at the mean of Asian men, the group with the highest rate of STEM degree attainment).

8.7. Separate Model

Tables A1 and A2 (in the Appendix A) examine the intersectional effects by running separate models for each of the eight gender and race groups. Table A1 focuses on the outcome of entry into a STEM field. The effects of academic preparations, and in particular, the highest math courses taken during high school, are very important for most of the groups. Family SES is less important. Table A2 focuses on the outcome of attaining STEM degrees. Here, the high school academic preparation, along with first year college GPA are important for most of the groups, and their impacts on life-STEM and physical-STEM fields are similar.

9. Conclusions

This study focused on entry to and attainment of bachelor's degrees in STEM fields, by examining gender and race/ethnicity in an intersectional manner. The intersectional analysis reveals that both race and gender matter in the STEM degree attainment. What is notable and consistent with previous research (Hanson 2009; Ma 2009; Riegle-Crumb and King 2010) is that black students were not at all under-represented at the starting point; that is, black males were as likely as white males to claim a STEM field as their initial major, and black females were more likely than white females to enter STEM. Black females in particular show their willingness, more than any other female groups, to choose physical-STEM fields as their initial college majors, in which females in general remain severely underrepresented. However, when it comes to completing a STEM bachelor's degree, the attrition issue for black students is severe. Asians and whites were much more likely to complete their bachelor's degree in STEM than blacks and Hispanics. Among those who had an initial major in STEM, females were slightly more likely than their male counterparts for all racial groups to complete the degree. Asian females had the highest persistence rate among all the groups, followed by Asian males.

Our findings reinforce the robust evidence provided by previous research that family and academic backgrounds are key to closing group disparities in STEM degree attainment. Our intersectional analytical approach can highlight particular race-gender groups that would benefit most from equalizing family and academic backgrounds. For example, women and racial minorities are the most under-represented in physical-STEM fields. Our analysis reveals that black men would have had the highest probability to graduate in physical-STEM fields, had they had the family and academic preparations of Asian males. Black women would have had the highest probability of graduating in physical-STEM fields among all women, had they had the family and academic preparations of Asian males. This highlights the critical importance of family resources and academic preparations, which improves the odds for STEM degree attainment for all groups. Black students would have experienced the most drastic progress.

The focus on both the starting and end points of a college career make it possible to pinpoint when and where minorities are under-represented, so that targeted efforts can be made. This study resonates with previous research showing that female students are more likely to persist in college once they are in a STEM field (Ma 2011). It also provides new evidence by looking at women in terms of race/ethnicity and finding that minority women share the same tendency of persistence with white women. This study also found that racial disparities in completing STEM degrees are much larger than at the entry point. Blacks and Hispanics, males and females included, trail behind Asians and whites in persistence. This study attempted to disentangle bachelor's degree attainment from STEM degree attainment. We found that for males, claiming a STEM major does not make much difference in the probability of dropping out of college; for females, claiming a STEM major was associated with a lower rate of dropping out of college than claiming a non-STEM major, which again testifies to the positive selection of females' choosing a STEM field.

Therefore, recruitment is much more important than retention for women at the undergraduate level. At the start of college, women are much less likely to choose a STEM major, and those who do are among the select few who are particularly driven and interested in STEM. Therefore, encouraging and supporting women as early as secondary school about the possibility of entering a STEM field is key for recruitment.

Our analysis extends earlier research on the trajectories of STEM degree attainment, by taking an intersectional perspective to examine race and gender. It not only corroborates with previous research that women are more likely to follow the non-dominant path, different from early entry and persistence as predicted by the pipeline model (Xie and Shauman 2003; Ma 2011), but also reveals that this non-dominant path of degree attainment applies to Asian women, Hispanic women, and white women. This provides further testimony that college may provide a more open environment that re-socializes women in a way that makes STEM fields more appealing and viable career path than pre-college does. This paper calls forth targeted efforts at pre-college stage to encourage and support women in STEM fields.

Other factors are noted as important in the literature, but we were not able to examine them given the scope of this project. In particular, the academic culture of STEM fields, especially the weed-out culture of STEM gateway courses and a lack of support overall, are integral to understanding racial disparities in persistence. The role of culture and climate in contributing to racial disparity in STEM is akin to a similar process leading to gender disparity in STEM (Catsambis 1994; Correll 2001). This indicates that efforts to improve the cultural climate in STEM fields and reduce the gender gap should be extended to address racial disparity.

Author Contributions: The lead author Yingyi Ma is in charge of research design, literature review and writing. The second author Yan Liu provides data analysis and some parts of the literature review and writing.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Multinomial Logistic Regression Models for Intersectional Effects (STEM Entry).

	Asian M		**Hispanic M**		**Black M**		**White M**	
	Life-STEM	**Physical-STEM**	**Life-STEM**	**Physical-STEM**	**Life-STEM**	**Physical-STEM**	**Life-STEM**	**Physical-STEM**
Family SES	1.011 (0.015)	1.014 (0.013)	1.007 (0.011)	1.006 (0.007)	0.976 (0.038)	1.003 (0.008)	0.960 (0.038)	0.994 (0.006)
Math test score	1.075 ** (0.038)	1.012 (0.027)	1.003 (0.033)	1.004 (0.020)	1.109 *** (0.042)	1.024 (0.025)	1.061 *** (0.014)	1.044 *** (0.010)
Highest math course	1.869 *** (0.363)	1.656 *** (0.240)	1.610 *** (0.297)	1.395 *** (0.162)	0.908 (0.231)	1.522 *** (0.240)	1.402 *** (0.097)	1.372 *** (0.069)
Observations	381	381	524	524	351	351	3019	3019
	Asian F		**Hispanic F**		**Black F**		**White F**	
	Life-STEM	**Physical-STEM**	**Life-STEM**	**Physical-STEM**	**Life-STEM**	**Physical-STEM**	**Life-STEM**	**Physical-STEM**
Family SES	1.010 (0.053)	0.687 (0.169)	0.999 (0.040)	0.903 (0.221)	0.997 (0.011)	0.997 (0.009)	0.994 (0.008)	0.998 (0.008)
Math test score	1.002 (0.030)	1.143 *** (0.053)	1.047 (0.036)	0.995 (0.031)	1.104 *** (0.041)	1.097 *** (0.034)	1.053 *** (0.014)	1.069 *** (0.018)
Highest math course	1.606 *** (0.280)	1.307 (0.290)	1.644 ** (0.328)	1.438 ** (0.266)	1.667 ** (0.375)	1.450 ** (0.270)	1.727 *** (0.125)	1.628 *** (0.141)
Observations	403	403	624	624	488	488	3482	3482

Reference group: "no major." Coefficients on "Non-STEM major" are not reported in this table. **denotes $p < 0.01$, ***denotes $p < 0.001$.

Table A2. Multinomial Logistic Regression Models for Intersectional Effects (STEM Degree Attainment).

	Asian M		**Hispanic M**		**Black M**		**White M**	
	Life-STEM	**Physical-STEM**	**Life-STEM**	**Physical-STEM**	**Life-STEM**	**Physical-STEM**	**Life-STEM**	**Physical-STEM**
Family SES	1.016 (0.014)	1.019 (0.012)	0.978 (0.069)	1.016 (0.012)	0.976 (0.074)	1.023 ** (0.010)	1.003 (0.007)	0.992 (0.010)
Math test score	1.144 *** (0.045)	1.074 ** (0.035)	1.059 (0.048)	1.062 (0.040)	1.147 *** (0.057)	1.047 (0.040)	1.080 *** (0.017)	1.107 *** (0.016)
Highest math course	1.976 *** (0.414)	2.498 *** (0.483)	2.467 *** (0.641)	2.932 *** (0.666)	0.860 (0.301)	2.250 *** (0.504)	1.807 *** (0.144)	2.157 *** (0.153)
GPA	2.447 *** (0.764)	2.933 *** (0.838)	2.247 * (1.073)	2.636 ** (1.059)	3.504 ** (1.828)	4.106 *** (1.639)	2.107 *** (0.277)	2.337 *** (0.267)
Observations	381	381	524	524	351	351	3019	3019
	Asian F		**Black F**		**White F**			
	Life-STEM	**Physical-STEM**	**Life-STEM**	**Physical-STEM**	**Life-STEM**	**Physical-STEM**		
Family SES	0.976 (0.038)	0.616* (0.166)	1.010 (0.011)	1.006 (0.012)	0.996 (0.010)	0.972 (0.056)		
Math test score	1.051 * (0.031)	1.172 *** (0.060)	1.053 (0.056)	1.057 (0.048)	1.113 *** (0.017)	1.180 *** (0.029)		
Highest math course	2.221 *** (0.395)	2.350 *** (0.661)	2.388 *** (0.754)	2.743 *** (0.752)	1.976 *** (0.150)	2.169 *** (0.248)		
GPA	2.256 *** (0.660)	1.293 (0.482)	2.999 ** (1.602)	2.977 ** (1.374)	2.010 *** (0.264)	2.314 *** (0.472)		
Observations	403	403	488	488	3482	3482		

Reference group: "no degree." Coefficients on AA and non-STEM degrees are not reported in this table. Due to the small sample size of Hispanic females in STEM degree attainment (less than 10), the estimates are unreliable, thus excluded from this table. **denotes $p < 0.01$, ***denotes $p < 0.001$.

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social sciences

Article

Weeded Out? Gendered Responses to Failing Calculus

Tanya Sanabria * and Andrew Penner *

Department of Sociology, University of California, Irvine, Irvine, CA 92697, USA
* Correspondence: tsanabri@uci.edu (T.S.); andrew.penner@uci.edu (A.P.)

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Abstract: Although women graduate from college at higher rates than men, they remain underrepresented in science, technology, engineering, and mathematics (STEM) fields. This study examines whether women react to failing a STEM weed-out course by switching to a non-STEM major and graduating with a bachelor's degree in a non-STEM field. While competitive courses designed to weed out potential STEM majors are often invoked in discussions around why students exit the STEM pipeline, relatively little is known about how women and men react to failing these courses. We use detailed individual-level data from the National Educational Longitudinal Study (NELS) Postsecondary Transcript Study (PETS): 1988–2000 to show that women who failed an introductory calculus course are substantially less likely to earn a bachelor's degree in STEM. In doing so, we provide evidence that weed-out course failure might help us to better understand why women are less likely to earn degrees.

Keywords: higher education; gender; STEM; inverse probability weighting

1. Introduction

A longstanding body of research on gender differences in education suggests that women are underrepresented in many science, technology, engineering, and mathematics (STEM) fields—particularly in the physical sciences and engineering (Xie and Shauman 2007). Research seeking to understand gender differences in who majors in a STEM field has identified a plethora of factors, ranging from discrimination, cultural stereotypes around gender and science, confidence, peer networks, and a preference for flexible curricula not offered in STEM departments (Correll 2001; Charles and Bradley 2009; Cech et al. 2011; Riegle-Crumb 2006; Mann and Diprete 2013). Underlying much of this research is the notion that STEM undergraduate training occurs in an environment that ranges from disengaging to competitive to chilly, and that this climate leads students to opt for other fields (Seymour and Hewitt 1997; Niederle and Versterlund 2007). While the factors that contribute to this climate are likewise numerous, competitive weed-out courses at the introductory level are a source of considerable dissatisfaction among undergraduates (Seymour and Hewitt 1997). These courses serve a gatekeeping function, as they are required for many STEM majors, and are often failed by a substantial number of students, promoting a competitive "sink or swim" environment (Seymour and Hewitt 1997; Kokkelenberg and Sinha 2010; Olson and Riordan 2012).

Importantly, both women and men see this as problematic. The women interviewed by Seymour and Hewitt express their thoughts like "I knew I could have done it if I wanted to. But I just said 'Do you really want to do this? Is it really worth killing yourself for?'" or "It's been unadulterated hell. Major overloads, no rest, stress—and it's getting worse. That's why I'm looking elsewhere" (Seymour and Hewitt 1997, pp. 202–3). Men's assessments are largely similar: "I mean, why stay [in science]? You know, there's no reason. And the rewards are—there's no rewards. I mean, I can see no logical reason why you'd stay." and "You go through hell in the sciences without any guarantee that you will be able to work. Why do it? Why not be an English major?" This sentiment is summarized by Meg Whitman, who noted in an interview that "I took calculus, chemistry, and physics my first year. I survived. But I didn't enjoy it ... After that, I had to find something else to do. I began selling advertising for a magazine that was published by Princeton undergrads. It was more fun than physics" (Fishman 2001).

However, despite the fact these weed-out courses are often invoked by students as a significant source of disengagement, surprisingly little is known about how undergraduates respond to failing these courses. While not examining weed-out course failure per se, research on grade inflation suggests that failing a weed-out class could play an important role in shaping students' future majors. One study, for example, found that students were "pulled away" by their higher grades in the humanities, arts, and social sciences courses and "pushed out" of STEM because of lower grades (Ost 2010). Grade inflation in introductory classes may be particularly important, as the grades that students receive in introductory courses strongly predict whether students choose to enroll in more courses in the discipline (Ost 2010). Introductory courses in STEM departments tend to be among the lowest graded courses (Rask 2010). Simulations suggest that if the grading distribution in introductory science courses resembled the college average, there would be 2–4 percent increase in advanced science course taking in later semesters (Rask 2010).

We build on this research by examining whether there are gender differences in the rates at which men and women fail introductory calculus (which we henceforth refer to simply as calculus), and how they respond to failure. Calculus often serves a gatekeeping function across STEM disciplines, limiting the rate at which students can take advanced coursework in their major. Introductory math courses, such as calculus, were found to be important factors for students' decisions to stay or switch out of STEM (Chen 2013). Although several studies have indicated that performance in introductory courses has been linked to STEM persistence, little attention has been given to failing weed-out courses like calculus. A key limitation in previous research is that these studies pool grades across STEM courses, using GPA as an indicator of poor performance. While important, these studies cannot ultimately address the role of weed-out course failure. Given the important signal that failing a weed-out course provides to students (Crisp et al. 2009), we argue that examining the gendered responses to calculus failure can provide researchers a better understanding of the critical junctures that shape a student's academic trajectory.

Gender might play an important role in shaping how students respond to failing calculus given societal stereotypes about math competence. Correll (Correll 2004) shows that beliefs about gender differences in a domain can shape self-assessments of competence and interest in pursuing a career using these skills. Specifically, when women are exposed to the belief that men are superior in a particular domain, women rate their performance worse than men, even when men and women receive identical feedback about their actual performance in the domain. Given widespread stereotypes about gender differences in mathematics, Correll's findings suggest that women who fail a calculus course might perceive their math skills to be worse than men who fail, and might have less interest in pursuing math-dependent careers. Gender differences in self-assessments driven by these stereotypes may explain why women tend to express doubts in their mathematical skills (Charles and Bradley 2009; Noel-Levitz 2014) and are more likely to switch to a female-typed major when receiving lower grades in coursework (Rask and Tiefenthaler 2008). As Charles and Bradley (Charles and Bradley 2009, p. 926) note, "Beliefs about gender difference can thus spawn powerful self-fulfilling prophesies".

While previous research suggests that women are more likely to re-evaluate and change their career pathways in response to negative feedback, we know of no study that has examined the implications of calculus failure and gender differences on whether students major in STEM. This study uses a doubly robust inverse probability weighting approach to compare the degree outcomes of students who had taken and failed calculus to a comparison group who passed calculus. We thus provide the first examination of the potentially gendered ways in which students responded to failing weed-out coursework.

Research Questions

Our key research question examines whether there are gender differences in the response to failing calculus, focusing on students' likelihood of completing a bachelor's degree, and in particular, on degree completion in a STEM field. To motivate the analyses for our central research question, we first ask (1) who takes and who fails calculus? Then, we ask, (2) what are the schooling outcomes associated with failing calculus? Finally, we address our key question, (3) are there gender differences in the schooling outcomes associated with failing calculus? To understand how failing a weed-out class may affect students in the STEM pipeline (i.e., those who may be considered at risk of majoring a STEM field), we narrow our sample size for questions (2) and (3) to students who planned to major in STEM as high school seniors.

2. Data

Data are from the National Education Longitudinal Study (NELS:88) and the NELS Postsecondary Education Transcript Study (PETS:2000) (NCES 1988; NCES 2000). The NELS:88 is a longitudinal study that followed a representative sample of 25,000 eighth-grade students over twelve years starting in 1988. The Educational Testing Service created pencil-and-paper tests to assess each eighth-grader's skills in reading and mathematics for the NELS:88. These tests were repeated in tenth, and twelfth grades. We use the student's percentile rank in the pencil-and-paper test in twelfth grade to measure students' pre-college academic skills in reading and math.

During each follow-up survey, additional data and interviews were collected from parents, teachers, and students participating in the study. As a longitudinal panel study, NELS:88 experienced sample attrition and non-response bias. To adjust for the sampling frame, the NELS:88 replenished the sample with additional respondents. All analyses thus use weights to adjust for these differences and students in the analyses were non-missing in key outcome, predictor, and control variables.

The fourth and last follow-up study of NELS:88/2000 for the sample of the eighth-grade class of 1988 occurred in 2000. The study collected postsecondary education transcripts for the sample members who responded to the final follow-up and reported attendance at a postsecondary educational institution in the third (1994) or fourth (2000) follow-up. Approximately 16,020 postsecondary transcripts were collected for 15,240 sample members, a subsample from the third follow-up. Transcripts contained detailed information on students' coursework, credits, grades, and degree obtained. To examine postsecondary education outcomes, we restricted our sample to the base-year through fourth follow-up studies, limiting the number of valid cases with a postsecondary transcript record to 7050 individuals.

3. Measures

Our key independent variable is failing an introductory calculus course, a key gate-keeping course that often serves as a requirement for STEM majors. Calculus courses were identified using the 2010 College Course Map (CCM) taxonomy system to code information on the course subject and title from college transcripts. Students were coded as having failed a class if they both (1) received a grade of "0" or "F" for the course and (2) reported zero earned credits for the course. We ran additional analyses where we define failure to include grades of "D", "D-", and "F". Findings were consistent with results from analyses reported here.

The two main outcome variables in this study are whether a student completed a bachelor's degree and whether they graduated with a bachelor's degree in a STEM field. STEM majors include engineering, mathematics, physics, chemistry, and biology; a complete list of majors included as STEM fields is available in Appendix A (Table A1). The degree type and major is reported on the student's transcript at collection.

We also control for a wide range of variables. Student-level controls include race/ethnicity, gender, socio-economic status, high school GPA (standardized), twelfth grade test score percentile ranks in both reading and math, whether students planned to major in STEM as high school students, and the highest math course taken while in high school. During students' senior year of high school, students were asked if they expected to attend college and in which field they expected to major; we collapsed anticipated majors into an indicator for whether students planned to major in a STEM field. While we would ideally use a measure of intended major from the fall when students entered university, we prefer our measure from the senior year of high school to information collected in the third follow-up of NELS:88 in 1994, when most students were in their second year of college.

We also control for whether the student's primary institution was a public two-year, private not-for-profit four-year, and a public four-year institution. Because some students move from one college to another, we coded for the first college that a student entered after high school. Accounting for observable differences on these dimensions helps ensure that the associations we observe between failing calculus and degree receipt are not being driven by these factors.

4. Sample

The first column of Table 1 provides a summary of the controls and outcome measures, as well as the number of students who took calculus and the number of students who failed (n = 3650). The study sample has slightly more women (52.6 percent) than men (47.4 percent). The sample consisted of primarily Non-Hispanic White (74.5 percent), with 7.5 percent identifying as Non-Hispanic Black, 11.5 percent identifying as Hispanic, and 6.6 percent as Asian. The average age that students entered college was 18.4, with ages ranging from 17 to 24.

To measure socioeconomic status, we use the socioeconomic status composite measure created by NELS, which combines information from the father's education level, mother's education level, father's occupation, mother's occupation and family income from the parent questionnaire data in NELS:88. In our sample, the average socioeconomic status (SES) composite is 0.08, meaning that the college-going students in our sample are relatively advantaged compared to the unweighted national average of −0.08 in NELS:88. For pre-college academic skills, we use the score percentile rank from the NELS pencil and paper test in reading and math that students took in twelfth grade in high school. On average, students in our sample of college-going students scored in the 60th percentile, meaning that students in our sample scored on average at the 60th percentile of the national distribution of high school seniors. The average high school grade point average (GPA) for our sample is 2.89. In our full study sample, about a quarter of students (24.9 percent) planned to major in STEM. We also take into account the highest level of mathematics course taken in high school, creating a series of indicators for whether students' highest math course was Algebra I or similar (10 percent), geometry (13 percent), Algebra II (34 percent), Trigonometry (15 percent), pre-Calculus (16 percent), or Calculus (12 percent).

Looking at institution-level characteristics, we see that approximately 38 percent of the students in our sample entered a public two-year institution as their primary institution, while 18 percent entered a private not-for-profit four-year institution, and around 45 percent entered a public four-year institution. Approximately 15 percent of the entire sample had taken calculus and 1.6 percent of the entire sample (10.7 percent of calculus takers) had failed calculus. Regarding key outcomes, about less than half of the sample (41 percent) had earned a bachelor's degree in any field as of 2000, while 46 percent did not. About 13 percent of the sample received a bachelor's degree in a STEM field.

The second and third sets of columns of Table 1 provide the summary of covariates, outcome measures and independent variables among students who planned to major in STEM (n = 910) and those who did not plan to major in STEM (n = 2740), respectively. The group of students who planned to major in STEM is more evenly split by gender (49 percent men and 51 percent women) compared with the group of students who did not plan to major in STEM (47 percent men and 53 percent women). There are fewer White students (70 percent as compared with 76 percent), more Black students (10 percent as compared with 7 percent), fewer Hispanic students (11 percent compared with 12 percent), and more Asian students (9 percent as compared with 6 percent) in the group of students who planned to major in STEM. Students who planned to major in STEM demonstrate slightly higher levels of pre-college academic skills (scoring on average at the 63rd percentile compared with the 60th percentile) and achievement (2.98 GPA compared with 2.86) than those who did not plan to major in STEM fields. A significantly larger proportion of students who planned to major in STEM had taken Calculus as their highest math course in high school (20 percent) compared to those who did not plan to major in STEM (10 percent) while a higher proportion of students who did not plan to major in STEM fields had taken up to Algebra II (36 percent compared with 29 percent).

Table 1. Descriptive statistics of variables used in analyses (n = 3650).

	Full Study Sample		**Planned to Major in STEM**		**Did Not Plan to Major in STEM**	
	# valid obs	**mean/%**	**# valid obs.**	**mean/%**	**# valid obs.**	**mean/%**
	3650		910		2740	
Gender						
Male	1730	47.4%	450	49.5%	1280	46.7%
Female	1920	52.6%	460	50.5%	1460	53.32%
Race/Ethnicity						
White (Non-Hispanic)	2720	74.5%	640	70.5%	2080	75.8%
Black (Non-Hispanic)	270	7.5%	90	10.2%	180	6.6%
Hispanic	420	11.5%	100	10.6%	320	11.8%
Asian	240	6.6%	80	8.7%	160	5.8%
Age when entered college	3650	18.4	910	18.3	2740	18.4
Socioeconomic status (composite)	3650	0.08	910	0.04	2740	0.09
Prior Ability and Achievement						
NELS test score percentile	3650	60.6	910	62.6	2740	60.0
High School GPA	3650	2.89	910	2.98	2740	2.86
Highest Math Course Taken in High School						
Algebra I or equivalent	380	10.3%	80	8.%	300	11.0%
Geometry	480	13.2%	100	11.0%	380	13.7%
Algebra II	1250	34.2%	260	28.5%	990	36.1%
Trigonometry	550	15.1%	130	14.3%	420	15.3%
Pre-calculus	570	15.6%	170	18.7%	400	14.6%
Calculus	430	11.8%	180	19.8%	260	9.5%
Primary Institution Type						
Public 2 year	1380	37.8%	340	37.3%	1040	38.0%
Private Not-For Profit 4-year	640	17.5%	150	16.5%	490	17.9%
Public 4-year	1630	44.7%	430	47.3%	1200	43.8%
Planned to Major in STEM						
Did not plan to major in STEM	2740	75.1%	–	–	–	–
Planned to major in STEM	910	24.9%	–	–	–	–
Calculus Course						
Taken calculus	560	15.3%	250	27.5%	300	11.0%
Failed calculus	60	1.6%	40	4.4%	30	1.1%
Degree Attainment						
Earned a bacherlor's degree	1510	41.4%	360	39.6%	1150	42.0%
Did not earn a bacherlor's degree	1660	45.5%	400	52.7%	1260	46.0%
Earned a Bachelor's in STEM						
Did not earn bacherlor's degree in STEM	1190	32.6%	150	16.5%	1050	38.2%
Earned bacherlor's degree in STEM	470	12.9%	250	27.5%	220	8.0%

Source: National Educational Longitudinal Study (NELS:88) and Postsecondary Education Transcript Study (PETS:2000) (NCES 1988; NCES 2000). Sample restricted to students who had valid non-missing information on their postsecondary enrollment status, coursework, institution type, gender, race, age, NELS 12th grade test score percentile, high school GPA, highest math course taken in high school, and orientation towards majoring in a science, technology, engineering or mathematics (STEM) field in college. Degree attainment does not include students who earned an Associate's Degree. n in models have been rounded to the nearest 10 for disclosure.

The percentages of students who entered a public two-year, a private not-for-profit four-year, or a public four-year institution as their primary institution in each group were fairly similar to the full sample. Approximately 28 percent of students who planned to major in STEM took calculus in college compared to 11 percent of students who did not plan to major in STEM. Four percent of students who planned to major in STEM as high school seniors had failed calculus, while one percent of students who did not plan to major in a STEM field failed calculus. The percentages of students who earned a bachelor's degree in each group were fairly similar to the full sample. Approximately 28 percent of students who planned to major in STEM earned a bachelor's degree in a STEM field, while 8 percent of students who did not plan to major in STEM earned a STEM bachelor's degree.

5. Methods

Estimation Strategy

We use doubly robust inverse probability weighting (IPW) to examine the relationship between failing calculus and degree outcomes among calculus takers. In our observational data, we cannot randomly assign our treatment (e.g., calculus failure). As such, students who fail calculus are likely to be different from those who did not fail calculus (our "control" condition) in both observable and unobservable ways. Table 2 provides descriptive results on students who take and fail calculus in the study sample. We see in Table 2 that there are both demographic and institutional differences between students who pass and students who fail calculus. Given these differences, we cannot estimate the effect of calculus failure on degree completion by simply comparing the estimates of degree completion likelihood among those who failed or students who passed calculus. To address this issue, we use IPW estimates to account for differences in the observable characteristics of students who pass and fail calculus.

IPW estimators use a two-step approach. First, the predicted probability of receiving the treatment is estimated for each student. Then, weights for each student are created. To balance the groups on observable characteristics, the IPW scheme up-weights students who received a given treatment but were unlikely to receive the treatment based on observable characteristics (e.g., students who were likely to fail but passed, or who were likely to pass but failed). Conversely, the scheme down-weights students who were highly likely to receive the treatment they received.

One limitation of IPW is that it assumes that the model used to predict the treatment (and therefore the weight) is correctly specified. If this model is not correctly specified, then the weighting will not account for the differences in these observable characteristics. We can relax the model specification assumption by using doubly robust IPW estimators and include controls in our weighted models predicting our outcomes. In these models, if either the weighting model or the final model is correctly specified, we will account for potential imbalance in our observable characteristics. It is important to clarify, however, that doubly robust models do not account for differences in unobserved characteristics of respondents. For a step-by-step process of how we created the doubly robust IPW estimators, see Appendix B.

6. Results

6.1. Predicting Calculus Taking and Performance

Table 2 presents the results of linear probability models in order to provide descriptive information on the characteristics of students who (a) take calculus compared to the entire study sample (n = 3490) and (b) fail calculus compared to students who had passed calculus (n = 540).

Model 1 shows that women are 11 percentage points less likely to take calculus than men, and that Asian students are nine percentage points more likely to take calculus than white students. A one-unit increase in SES composite is associated with a two percentage-point increase in taking calculus. One percent increases in students' reading and math scores and high school GPA are associated with four and 11 percentage-point increases in the likelihood of taking calculus, respectively. Compared to students who had algebra I or a similar course as their highest math class in high school, students who took algebra II are, if anything, slightly less likely to take calculus, while students who took calculus in high school were 31 percentage points more likely to take calculus in college. Students who planned to major in STEM as high school seniors were 13 percentage points more likely to take calculus. Finally, students entering a four-year private or public college (compared to entering a two-year college) were six and three percentage points more likely to take calculus, respectively.

Table 2. Linear Probability Models (LPM) predicting who takes calculus and who fails calculus.

	Taken Calculus	**Failed Calculus**
	Compared to Students Who Never Took Calculus	**Only among Students Who Took Calculus**
Demographics		
Female	−0.11 *** (−8.20)	−0.02 (−0.44)
Age	−0.38 (0.11)	−0.76 (−1.46)
Age squared	0.01 (0.11)	0.02 (1.50)
Black	0.01 (0.68)	−0.01 (−0.81)
Hispanic	0.01 (0.60)	0.01 (0.15)
Asian	0.09 * (2.31)	0.07 (0.84)
Socio-economic status composite	0.02 * (2.21)	−0.06 * (−2.11)
Prior academic skills and achievement		
NELS 12th grade test score percentile (logged)	0.04 *** (4.69)	−0.03 (−0.45)
High school GPA (logged)	0.11 *** (4.27)	−0.17 + (−1.70)
Highest math course taken in High School		
Geometry	−0.03 (−1.64)	−0.20 (−1.06)
Algebra II	−0.02 + (−1.76)	0.07 (−0.35)
Trigonometry	0.04 + (1.90)	−0.07 (−0.37)
Pre-calculus	0.10 *** (3.77)	−0.11 (−0.59)
Calculus	0.31 *** (8.75)	−0.12 (−0.65)
Planned to major in STEM	0.13 *** (7.23)	0.03 (0.74)
Institution Type		
Private not-for-profit 4-year	0.06 ** (2.62)	0.05 (1.23)
Public 4-year	0.03 * (2.18)	0.11 * (2.37)
Constant	3.37 (7.23)	7.53 (1.55)
R^2	0.24	0.11
n	3490	540

Source: National Educational Longitudinal Study (NELS:88), Postsecondary Education Transcript Study (PETS:2000) (NCES 1988; NCES 2000). t-statistics underneath coefficients in parentheses. Controls are in reference to male, White, highest math course taken as Algebra I or other math course in high school, and entered a public two-year college. Sampling weight used in analyses. n in models have been rounded to the nearest 10 for disclosure. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Model 2 examines how the same set of factors from Model 1 are associated with failing calculus among students who took it. Importantly for our purposes, we see no gender differences in the likelihood of failing among calculus takers. We do find that high SES students, as well as students with higher GPAs in high school are less likely to fail. We also find that students who directly enter a four-year college are more likely to fail than students who first entered a two-year college. All other variables in the model yielded statistically non-significant findings.

6.2. General and STEM Bachelor Degree Attainment

Our results examining the relationship between failing calculus and degree attainment are presented in Table 3. As noted earlier, to focus on students who might plausibly be in the STEM pipeline, we restrict our analyses here to students who (a) planned to major in STEM in their senior year of high school and (b) had taken calculus in college. Students in this sample were weighted based on their probability of being assigned to treatment received. To address concerns around misspecification in the weighting model, we estimate doubly robust models that include all covariates in the models predicting our outcomes. In the first two models, we first examine whether students completed a bachelor's degree in any field. Models 3 and 4 examine whether students attained a bachelor's degree specifically in a STEM field.

Table 3. Linear Probability Models (LPM) predicting receipt of a bachelor's degree and receipt of a bachelor's degree in a STEM field, among students who had taken calculus and planned to major in STEM.

	Bachelor's Degree	**Bachelor's Degree**	**STEM Bachelor's**	**STEM Bachelor's**
Failed calculus	−0.12 $^{+}$		−0.12	
	(−1.66)		(−1.39)	
Gender and Failure Status				
(Omitted category: men—did not fail calculus)				
Men—failed calculus		−0.03		0.13
		(−0.34)		(1.30)
Women—did not fail calculus		0.12 $^{+}$		0.04
		(1.82)		(0.48)
Women—failed calculus		−0.19		−0.66 ***
		(−1.45)		(−7.40)
Constant	16.43	18.14	−52.37	−44.35
	(0.67)	(0.76)	(−1.52)	(−1.36)
R^2	0.25	0.27	0.31	0.42
n	230	230	190	190

Source: National Educational Longitudinal Study (NELS:88) and Postsecondary Education Transcript Study (PETS:2000) (NCES 1988; NCES 2000). STEM in reference to science, technology, engineering or mathematics fields. *t*-statistics underneath coefficients in parentheses. Reference category for interactions is a male college student who did not fail calculus. Includes demographic, prior achievement/academic skills, and institution controls for doubly robust estimates. n in models has been rounded to the nearest 10 for disclosure. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In Model 1, we examine the relationship between failing calculus and completing a bachelor's degree. After accounting for demographic characteristics, prior achievement, academic skill, highest math course taken in high school, and institution-level covariates, we find that failing calculus is associated with a 12 percentage-point decrease in degree completion. In Model 2, we interact failing calculus and gender to see whether the relationship between failing calculus and bachelor degree completion varies by gender. To facilitate interpretation, we present predicted probabilities from Model 2 (holding covariates constant so that covariates are averages for the study sample) in Figure 1. While we find only small differences in the likelihood of receiving a bachelor's degree between men who passed and failed calculus (0.80 versus 0.76), we see that women who did not fail calculus are 32 percentage points more likely to receive a bachelor's degree than women who failed calculus (0.92 versus 0.60; $p = 0.019$). Men's likelihood of receiving a bachelor's degree is thus not strongly tied to whether they pass calculus, while for women it is. Women who pass calculus are more likely to get a bachelor's degree than men, while women who fail calculus are less likely to do so.

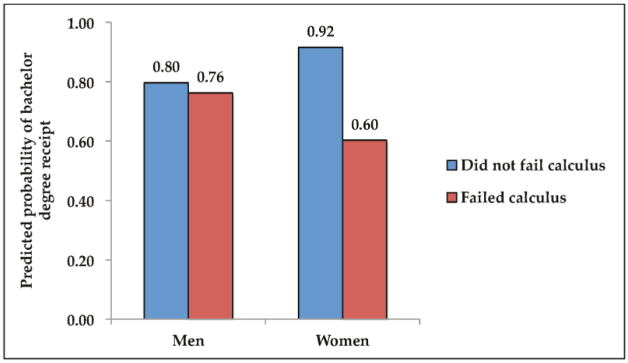

Figure 1. Predicted probabilities of bachelor degree receipt by gender. Source: National Educational Longitudinal Study (NELS:88) and Postsecondary Education Transcript Study (PETS:2000) (NCES 1988; NCES 2000).

Model 3 in Table 3 examines the relationship between failing calculus and STEM bachelor's degree completion. Here we find that, overall, failing calculus was not statistically significant (p = 0.165), though the point estimate is similar in magnitude and direction as in Model 1, suggesting that students who fail are less likely to obtain a STEM degree. Model 4 follows Model 2, examining the relationship between failing calculus and receiving a STEM bachelor's degree by gender. Predicted probabilities from Model 4 are reported in Figure 2. As above, we find no statistically significant differences among men (0.74 versus 0.86), but we do find that there is a statistically significant difference between women who do and do not fail (0.07 versus 0.78, $p < 0.001$). As is readily visible in Figure 2, failing calculus does not appear to weed out men, but does appear to weed women out.

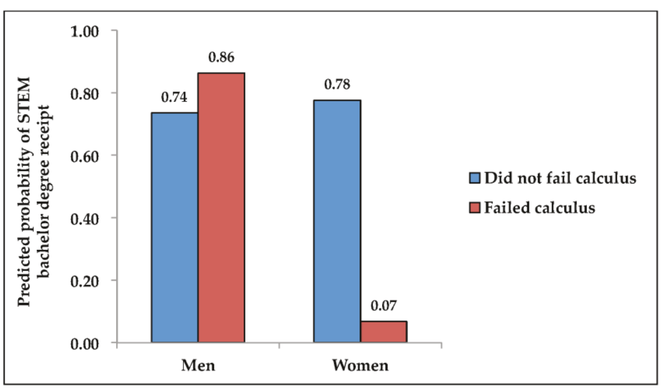

Figure 2. Predicted probabilities of bachelor degree receipt in a Science, Technology, Engineering, and Mathematics (STEM) field by gender. Source: National Educational Longitudinal Study (NELS:88) and Postsecondary Education Transcript Study (PETS:2000) (NCES 1988; NCES 2000).

7. Discussion

Despite widespread interest in the role of weed-out classes in the STEM training pipeline, little is known about how failing a weed-out class might shape both men and women's STEM decisions to major in a STEM field. Using nationally representative data and a wide range of controls, we find that women who intended to major in STEM and fail calculus in college are significantly less likely to obtain a bachelor's degree in a STEM field. For men who intend to major in a STEM field, on the other hand, we find no evidence that failing calculus lowers their likelihood of obtaining a STEM degree. To the degree that calculus functions as a weed-out class, our findings suggest that it does so in a profoundly gendered way, weeding out women but not men.

Our results have important consequences for policies aimed at increasing the representation of women in STEM fields. Given that calculus often serves as a gatekeeper for advanced courses in STEM, students who fail calculus face additional barriers that make it difficult to continue with their college studies in many STEM fields (Seymour and Hewitt 1997; Chen 2013). Our findings suggest that these barriers do little to dampen men's STEM degree completion, but may play a substantial role in shaping women's STEM degree completion. Policies aimed at increasing the representation of women obtaining STEM degrees may want to focus on women at this crucial stage, and efforts to assist students who have failed calculus may want to focus particularly on women. More broadly, given the lack of an effect on men's majors, these findings suggest that STEM educators may want to rethink the role of weed-out classes in STEM education. That is, it is difficult to argue that weed-out classes are doing their job and keeping unprepared individuals from pursuing these majors, when men who fail calculus are just as likely to graduate with a STEM degree as men who pass.

This lack of a difference for men is perhaps puzzling and raises additional questions. For example, it is unclear at what rate we would want men and women who failed calculus to continue pursuing STEM degrees (Penner and Willer 2015). Women are generally more responsive to grades than men (Charles and Bradley 2009), and while research on STEM persistence typically operates under the assumption that STEM persistence should be encouraged for all individuals, it seems plausible that after failing a weed-out class, pursuing a different major is potentially more adaptive than continuing to major in STEM. That is, while qualities like grit (Duckworth et al. 2007) and resilience (Masten 1994) are rightfully celebrated, adaptive goal disengagement (Heckhausen and Schulz 1995) is also an important adaptive strategy. To use a non-educational example, somebody who has repeatedly asked a romantic interest to go on a date and been turned down should potentially disengage from the goal of being in a romantic relationship with this individual, rather than continue to persist. While we are unable to adjudicate whether the women who fail weed-out classes are best served by persisting in STEM fields, we argue that understanding the outcomes associated with weed-out class failure provides insight into the larger structural changes needed to alter students' persistence decisions.

In line with arguments around adaptive goal disengagement, our findings could in part also reflect the fact the women who fail calculus have better non-STEM options than men (Penner 2015; Wang et al. 2013). If this was the case, weed-out classes could plausibly explain both why women are less likely to major in STEM fields (they switch their majors after failing) and why men are less likely to graduate from college, net of enrollment rates (if they drop out after failing a weed-out class). As we only find evidence for the first of these processes, this suggests a gendered dimension in how calculus weeds women out of STEM fields. It also seems unlikely that these differences could produce differences of the magnitude we observe here. However, this perspective does highlight that we should not view women dropping out of the STEM pipeline as failures, but instead focus on questions around how STEM fields are structured.

In addition to questions about the larger structure of STEM education, larger societal stereotypes about gender and STEM are potentially relevant. One explanation for our findings is that the weed out culture for introductory-level coursework combines with gendered stereotypes about STEM fields to result in different self-assessments after calculus failure (Correll 2004). That is, much like the women in Correll's study who expressed less interest in pursuing fields that were said to be male advantaged, larger gender stereotypes might shape how women who fail calculus incorporate this information into their self-assessments and interests differently than men.

In supplemental analyses, we considered whether failure in any course deters women from earning a STEM degree. Taking a sample of students in the humanities "pipeline," we estimated whether failing introductory writing composition is more likely to deter women than men from graduating with a humanities degree using the same IPW estimation strategy described above. While failing introductory writing is negatively associated with completing a bachelor's degree and a humanities bachelor's degree, we find no gender differences in humanities degree attainment rates among those who failed this course. We also examined other potential STEM weed-out courses (e.g., introductory chemistry), and do not find similar patterns in these courses as for calculus. This is perhaps surprising, and may speak to the unique space that calculus occupies.

8. Limitations

While we provide important evidence regarding the different ways in which women and men respond to failing weed-out courses, our study has several limitations. The first is the possibility that students who have failed calculus are different from students who did not in unobservable ways, limiting causal attributions. While we account for a wide range of observable characteristics by estimating doubly robust IPW, our approach cannot account for unobserved differences between the students who did and did not fail calculus.

Another limitation of our study is our lack of information about students' intended majors before and after taking calculus. We use information about whether students planned to major in STEM as high school seniors to indicate whether students could be in the STEM pipeline at this point, but cannot isolate failing calculus as being the factor that led students to pursue a different major. For example, we lack information on other important factors associated with college and STEM persistence, such as quality of faculty-student contact in the STEM department, peer interactions, experiences or perceptions of diversity on the college campus, student satisfaction, and participation in extracurricular activities while enrolled in college (Seymour and Hewitt 1997). Of particular note, we lack data on perceptions of failure, motivation, and self-efficacy in the NELS:88 (Tinto 1987). However, to the degree that many of these considerations could be mediators that helped explain why failing mattered, it is unclear that they should be introduced as control variables. Additionally, while we acknowledge that calculus takers across STEM majors may differ, the limited sample size in our study does not allow separating out analyses by specific major (e.g., physical versus biological sciences).

Finally, although we use a large, nationally representative dataset to examine these questions, the number of individuals who intended to major in a STEM field and took (and failed) calculus is relatively small, necessitating caution in interpreting the results. As such, these results would benefit from future replication studies. Furthermore, as noted above, in our supplemental analyses, we find evidence suggesting that calculus may be unique, as we do not find similar patterns for other introductory STEM courses. However, given the relatively small samples for these classes, future work on this question would be particularly useful in understanding if other attributes to its position in the course sequence, course content, pedagogy or other factors play a role in weeding out women but not men. In particular, while we focus on calculus, given its prominent position and relative prevalence, future work might fruitfully examine whether other weed-out classes function in similar gendered ways.

9. Conclusions

Gender disparities in postsecondary STEM education continue to be an enduring issue in higher education. Our study examined how men and women react differently to failing a weed-out course among potential STEM majors, which might shape their educational pathways. Using detailed individual-level data from NELS PETS:1988–2000, we find that women who planned to major in STEM and failed calculus in college were substantially less likely to obtain a bachelor's degree in STEM. On the other hand, failing calculus did not appear to lower the likelihood of STEM degree receipt among men. Thus, we demonstrate evidence of the gendered ways these weed-out courses function—weeding out women but not men in the STEM degree pipeline.

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Appendix A

Table A1. Coding for Expected Majors and Received Majors as STEM.

Planned to Major in STEM	Did Not Plan to Major in STEM
Architecture and Related Programs	Agricultural Business and Production
Biological and Life Sciences	Area, Ethnic and Cultural Studies
Computer and Information Sciences	Business Management
Engineering	Communications
Engineering Related Technologies	Education
Mathematics	Health Professions
Physical Sciences	Humanities
Science Technologies	Law
	Liberal Arts and Sciences
	Public Administration and Services
	Reserve Officers' Training Corp (R.O.T.C)
	Social Sciences
	Vocational Education
	Visual and Performing Arts

Appendix B

Doubly Robust Inverse Probability Weighting

In the first step of doubly robust IPW, we estimate propensities (P) for each student. Using covariates discussed earlier, each student is given a propensity score. An individual variable does not have to be a statistically significant predictor of treatment in the propensity model since the objective is for students in the treated and control categories to be balanced on the covariates. The propensity score equation is a logit model predicting the probability of a student receiving an F in calculus. All individual-level and college-level covariates discussed above were included in the logistic regression equation to predict the probability of treatment:

$$Pr(Fail)_i = \alpha_i + \beta_k \mathbf{X}_{ki} + \varepsilon_i. \tag{A1}$$

Equation (A1) predicts the probability of a student failing calculus in college and $\mathbf{X}_\mathrm{i}$ is a vector of control variables. In the model above, i represents the value of an individual in the predictor equation.

After estimating each student's predicted probability of failing calculus in Equation (A1), we then use the probabilities to create inverse probability weights, which we define as the inverse of the probability of receiving or not receiving the treatment given observable characteristics. For students at each category of treatment t (failed or passed calculus), we define our inverse probability weight as:

$$W = 1/\hat{P}_t, \tag{A2}$$

where $\hat{P}_t$ is the predicted probability that a student received the treatment that he or she received.

For doubly robust IPW estimators, the same covariates used to estimate the probability weights for Equation (A1) are also included as controls in a linear probability model predicting our degree outcomes. To examine whether the relationship between failing calculus and degree outcomes vary by gender, we estimate models that interact failing calculus with gender. We estimate two sets of these models; the first set predicts bachelor degree completion in any field and the second set predicts STEM bachelor degree completion. Thus, our first model in Table 3 predicts whether students completing a bachelor's degree in any field as a function of failing calculus:

$$Pr(Degree)_i = \alpha_i + \beta_1 Fail_i + \beta_k \mathbf{X}_{ki} + \varepsilon_i \,, \tag{A3}$$

where $Fail_i$ is a dummy variable equal to one if a student ever failed calculus and zero otherwise and $\mathbf{X}_i$ is a vector of background controls for doubly robust estimates. The main effect of $Fail_i$ provides information about the association between failing calculus and receiving a bachelor's degree. In the next model, we include an interaction effect between $Fail_i$ and whether the student was female to examine the association any variation between failing calculus and bachelor degree completion by gender. The error term, ε_i, captures characteristics not accounted for in the model that influences the outcome variable. We estimate similar models predicting STEM bachelor degree receipt.

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Article

Gender Differences in the Early Employment Outcomes of STEM Doctorates

Kimberlee A. Shauman

Department of Sociology, University of California, Davis, CA 95616, USA; kashauman@ucdavis.edu;
Tel.: +1-530-754-0773

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Abstract: The representation of women among STEM doctorates has grown over the past decades but the underrepresentation of women in the STEM labor force persists. This paper examines the immediate post-degree employment outcomes of nine cohorts of STEM doctorates who attained their degrees between 1995 and 2013. The results reveal both progress toward gender equity and persistent inequities. Contrary to historical gender disparities, a small female advantage has emerged in the attainment of tenure-track faculty positions, women are increasingly less likely than men to enter postdoctoral positions, and the flow of STEM doctorates into business and industry, which was once male dominated, is now gender neutral. Among the doctorates who do not follow the doctorate-to-faculty career path, women are as likely as men to "stay in STEM," but less likely to attain research-oriented jobs. Gender segregation in occupational attainment and significant gender gaps in earnings, however, continue to be defining characteristics of the STEM labor force. The results show that the labor market disparities vary across STEM fields but are largely not attributable to the gendered impact of parenthood and dual-career marriage.

Keywords: gender; STEM; labor market; family; trends; segregation

1. Introduction

The representation of women among doctorates in science, technology, engineering and mathematical (STEM) fields has grown significantly over the past decades [1] but the underrepresentation of women in the STEM labor force persists [2]. Women with STEM doctorates are less likely than men to work in STEM occupations, and those who do are less likely to be employed in the most prestigious and well-paid positions in academia, government, business and industry [3,4]. The observed gender inequalities in the STEM labor force are generated by myriad influences and sorting processes operating continuously throughout the life course [3], but recent evidence points to the critical and long-term impacts of the immediate post-degree transitions. For example, a primary cause of the continued underrepresentation of women among recent cohorts of research university faculty is that women may be less likely than men to apply for faculty positions [4,5]. Identifying the extent, character and causes of gender differences in early employment transitions is therefore central to understanding gender differences in the STEM labor force and developing policies that support the optimal and equitable development of STEM talent.

In this paper, I present a detailed analysis of the immediate post-degree transitions of doctorates in STEM fields, using data from nine cohorts of doctorates from the 1995–2013 waves of the *Survey of Doctorate Recipients* (SDR). I focus on the transition to the labor market within two years of Ph.D. completion and examine gender differences in multiple employment outcomes that capture the full range of post-degree labor market experiences that may impact career development. This analysis is motivated by 4 research questions:

- Are there gender differences in the immediate post-degree labor market outcomes of STEM doctorates?
- Which labor market outcomes have the greatest gender disparities?
- Have the observed gender disparities changed over time?
- Do the gender differences in labor market outcomes vary by STEM field, and are they associated with the doctorates' family characteristics?

This analysis is largely descriptive in that I identify where the labor market experiences of women and men differ and if those differences are correlated with a set of variables measuring the family characteristics of the STEM doctorates. By disaggregating the transition to the labor market and examining gender differences across multiple aspects of early employment, I provide a more nuanced assessment of the degree to which women are less likely to utilize their educational investments and to leave the STEM labor force. I focus on assessing the influence of family characteristics on gender differences in employment outcomes because prior research identifies parenthood and other family characteristics, e.g., dual-earner couple status, as having particularly negative effects on women's employment outcomes in the STEM fields. The demands of childbearing and of caring for young children appear to have a particularly negative influence on the likelihood that women will stay in STEM fields and attain career success on a par with their male colleagues [3,6,7]. Research has also identified employer behaviors, such as unconscious bias against women in general [8–10], and against mothers in particular [11], along with structural and cultural aspects of STEM workplaces [12] that operate on the demand-side to inhibit the career progress of women.

This study is designed to address four empirical limitations of prior research. First, analyses of gender differences in STEM tend to focus on single employment outcomes and to collapse all alternatives into a single comparison category. Such simplistic operationalizations of the transition process can identify neither the relative probability of competing employment outcomes nor the correlates of those outcomes. The employment outcome that has received the most attention is the attainment of a tenure-track job, and the focal question is: why are women *not* attaining/choosing academic jobs? Analyses addressing this question often use a dichotomous classification of employment outcomes, academic vs. non-academic positions, which obscures the heterogeneity among the alternatives to academic employment. When a clearly-defined outcome is contrasted with a heterogeneous aggregation of "other" outcomes, only the characteristics of the focal employment outcome and the influence of correlates associated with its achievement can be measured with accuracy. Studies that employ this strategy cannot adequately address why women choose non-academic jobs, what characteristics of non-academic jobs they attain, and how they fare in those jobs relative to men. Studies that focus on the academia-vs.-other dichotomy also reify the assumptions that employment in academia is the most desirable outcome and that other types of employment represent a "loss" at both the individual and institutional levels—individual women disproportionately "lose" in the competition for academic employment and the science pipeline "loses" women disproportionately. This assumption is further bolstered by a tendency for the research to focus on factors that might "push" women out of academia (e.g., chilly climate, incompatibility of academia with family formation, etc.) [13–15] and to neglect positive aspects of non-academic employment options that might "pull" women to other sectors of STEM employment.

Second, the study of differences in employment outcomes tends to ignore the dynamic and contingent nature of career development. Despite the universal adoption of the "pipeline" characterization of the science career trajectory, the study of gender differences in STEM is segmented into literatures that focus on distinct career stages but rarely examine the transitions between those stages [3]. The contingent nature of the successive stages of the career trajectory is acknowledged but not often incorporated into analyses. Research commonly compares the representation of women at prior stages in the trajectory to their representation at a subsequent stage without attending to the intervening transitions that condition the likelihood of the focal outcome. Yet inattention to intervening transitions may produce biased estimates of gender differences and misidentification of their causes.

It is common, for example to compare the percent female among tenured faculty with the percent female among doctorates to assess the size of the gender gap in the tenure rates. The appropriate denominator for the calculation of gender differences in the tenure rate is a much-debated topic that hinges on the degree to which the transitions that intervene between degree attainment and achievement of tenure are acknowledged. Estimated gender differences in the rate of tenure attainment will vary from large to non-existent depending upon whether the denominator of the rate is all doctorates, doctorates who enter the labor force, doctorates who apply for tenure-track positions, or just the doctorates who attain a tenure-track position. Analyses of career outcomes that ignore the nested or conditioning effect of intervening transitions are unlikely to accurately represent the career-building process and, therefore, to identify the component processes that generate gender-specific outcomes.

Third, extant research has tended to ignore the heterogeneity within science fields and across the labor market for doctorate-level scientists and engineers. The distribution of doctorates across the STEM fields is significantly segregated by gender and since post-doctorate career pathways are also field-specific, gender segregation will yield significant aggregate-level gender differences in employment patterns. However, there is ample evidence of significant gender differences in academic employment, rates of promotion to tenure, salary and other employment outcomes among doctorates in the same field [16–18]. These within-field gender differences in the career paths of doctoral scientists may be driven by influences that are unique to specific STEM fields. Analyses that aggregate science fields therefore risk obscuring or misrepresenting the magnitude of the gender differences that exist, and attributing gender differences in educational and occupational experiences in blanket fashion when they apply in only specific fields.

Fourth, prior research has measured "persistence in STEM" in a narrow way that may underestimate the degree to which women apply their STEM education in the labor market. Attaining a tenure-track faculty position at a research-intensive university is often characterized as the ideal labor market application of a STEM doctorate because such employment fully utilizes the educational capital the STEM Ph.D. represents. Other types of employment vary in the degree to which they utilize doctoral-level training in a STEM field and are part of "the STEM pipeline." Some jobs will rival the research university faculty position in their demand for specialized knowledge and skills, some will demand only some of the specialized training gained in the pursuit of a STEM doctorate, while the performance of others will demand none of that training. Identifying the degree to which the STEM doctorate is utilized in various occupational outcomes is therefore at the heart of our ability to reliably identify gender differences in the utilization of STEM education and participation in the science labor market. Prior research on gender differences in the "science pipeline," has relied on a researcher-imposed operationalization of educational utilization [3], by which researchers classify a set of occupations as those that comprise the STEM labor market, and employment in one of these occupations is defined as the utilization of STEM education. I propose and apply a more data-driven approach to identifying STEM-related employment for the analysis presented in this paper. See Appendix B for a discussion of the approach and Section 2.1.2 for a description of how it is applied in this study.

To address the limitations of prior research, I consider post-doctorate labor market entry as a set of contingent transitions that result in employment in a range of academic and non-academic settings. Figure 1 presents the conceptualization of the post-doctorate transition to the labor market that guides this analysis. I analyze gender differences in four nested employment outcomes and in the salary the doctorates earn 2 years after completing their degrees. The conditional nature of the labor market outcomes is reflected in the analytical design in that preceding states define the population at risk of subsequent outcomes.

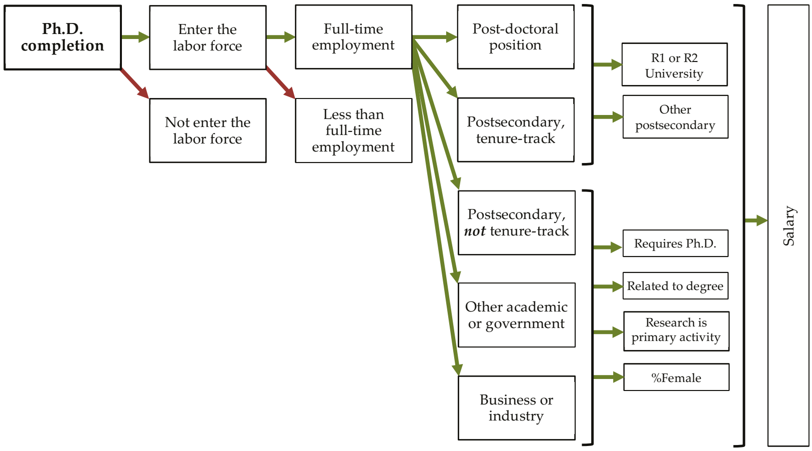

Figure 1. Schematic representation of post-doctoral employment transitions and outcomes.

Among the full population of STEM doctorates, all possible employment outcomes depend on whether a doctorate enters the labor market. Doctorates who enter the labor market and gain employment[1] may work full or part time, and since part-time jobs are not equally distributed across the labor market, the degree of labor force attachment has implications for the types of jobs doctorates may attain. Gender differences in part-time employment may therefore help explain other disparities in STEM labor force outcomes. Among full-time workers, STEM doctorates may enter a broad range of occupations which I classify as belonging to five discrete employment sectors: (1) postdoctoral positions; (2) tenure-track faculty positions in postsecondary educational institutions; (3) *non*-tenure-track faculty positions in postsecondary educational institutions; (4) other academic positions, including those in elementary and secondary school, and government positions; and (5) positions in business or industry. Although each of these categories offers opportunities to utilize the educational investments that the STEM doctorates have made by doing work that is related to their doctoral field and training, there is significant between-category variation in the types of jobs they offer. The five categories also differ in the degree to which they capture a homogeneous set of jobs: the first and second categories are the most homogeneous, whereas the "other academic or government" and "business or industry" sectors are quite heterogeneous. I therefore distinguish different types of employment outcomes within each of these sectors. In light of the persistent underrepresentation of women among the faculties at research-intensive universities (those classified as R1 and R2 doctoral-granting institutions on the Carnegie Classification), and because the attainment of a postdoctoral position, especially at a research-intensive university, has become a necessary prerequisite a faculty position [19,20], I assess the likelihood of attaining employment at such institutions among the STEM doctorates who enter postdoctoral positions and tenure-track faculty positions. For doctorates entering the other three employment sectors, I examine the likelihood that they attain jobs where their educational investment is utilized—indicated by the degree to which the job requires a Ph.D., is closely related to their degree field, and research is a primary job activity. I also assess the degree to which the transition into these employment sectors is marked by gendered sorting by testing the association between the doctorates' gender and the gender-type of the occupations they enter, as measured by the percentage of females among incumbents.

1 Unemployment is negligible in the data, so labor force participation and employment are essentially equivalent.

The relationships between the employment outcomes specified in Figure 1 are more complex and recursive than depicted, but modeling the transition to the labor market as a discrete set of steps has a number of advantages. First, it reflects the contingent nature of the transition to the labor force by identifying the successively selective segments of the population of doctorates at risk of each type of outcome. Second, this approach to defining the population at risk of each outcome yields relatively conservative estimates of the gender gaps that characterize each and allows identification of where the gender gaps are greatest. Third, by considering both academic and non-academic employment outcomes, as well as those that are related and unrelated to doctoral degrees in STEM fields, this approach provides a more complete assessment of the career paths followed by STEM doctorates. It therefore can test the perception that women are disproportionately "lost" from science, and achieve a more nuanced assessment of how STEM doctorates utilize their educational investments.

I note that the conceptualization presented in Figure 1 includes two outcomes that are characterized as terminal (indicated by red arrows): the transition out of the labor force and part-time employment. These transitions do not, in fact, preclude full labor market participation but gaps in labor force participation and full employment do impact job placement, promotion rates and earnings trajectories [21]. However, I bracket such questions about gender differences in the experience and impact of these labor market states from this analysis.

2. Materials and Methods

2.1. Data

This analysis uses data from two sources: the 1995, 1997, 1999, 2001, 2003, 2006, 2008, 2010, and 2013 waves of the *Survey of Doctorate Recipients* (SDR) [22] and the *O*NET Occupational Information Network Database* (O*NET) [23]. The SDR is a longitudinal study of individuals who obtained a doctoral degree in a science, engineering or health field from a postsecondary institution in the U.S. The biennial survey conducted by the National Center for Science and Engineering Statistics collects information about the doctorates' demographic characteristics, educational background, employment situations, and other measures of career achievement. The SDR includes detailed classifications of both Ph.D. degree field and occupation, so it supports the identification of specific education-occupation transitions.

The SDR data supply both the analytical sample of recent STEM doctorates used to measure gender differences in the transition to the labor market and a sample used to operationalize three measures of job characteristics that are specific to the population of doctorates (see description in Section 2.1.2). Although the SDR is a longitudinal dataset, the sample used for this analysis is drawn from the "new cohort" of doctorates that is added at each new wave of the SDR. The analytical sample is therefore an aggregation of single-year, cross-sectional data snapshots of each new cohort of STEM doctorates, i.e., it does not incorporate the longitudinal nature of the data. Each new cohort includes approximately 5000 doctoral recipients who received their degree within two years of the survey date.[2] The analytical sample therefore includes a total of 18,687 doctorates, 12,953 men and 5,734 women aged 25 to 50 who had attained a doctoral degree within the 2 years preceding the survey, i.e., degrees earned in the years 1993 through 2011, who provided complete information about their employment status and occupation.

The occupation-level characteristics are aggregated from a larger 'operationalization sample' that includes all respondents from the SDR "older cohorts" who meet the following criteria: they are aged 25 to 50 years; they had attained a STEM doctoral degree 3 to 13 years prior to the survey date; they reported being employed and working 35 or more hours per week at the time of the survey; and they provided complete responses about their doctorate field, their occupation, and to a set of survey items

[2] The new cohort of the 2006 survey includes doctoral recipients who received their degree within three years.

soliciting their subjective assessment of the extent to which their job is related to their degree field and if research is a primary activity of their job. The operationalization sample drawn using these selection criteria consists of 63,962 individuals (47,700 men and 16,262 women) who earned their degree in the years 1982 to 2010. This sample includes multiple observations of individual doctorates and thereby provides the large sample required to generate reliable measures of occupational characteristics by degree field and year. I emphasize, however, that the operationalization sample is exclusive of the analytical sample of sample of STEM doctorates, so the measures of education-occupation relatedness are exogenous to the behavior of the STEM doctorates included in the analytic sample.

The O*NET data includes detailed information about the characteristics, requirements and activities of a broad range of occupational and worker attributes for jobs classified according to the Standard Occupational Classification (SOC) system that are gathered from on-going representative surveys of job incumbents [24]. I use these data to operationalize one of the job-level characteristics included in this analysis: the level of education required to perform a job (described in Section 2.1.2).

2.1.1. Individual-Level Variables Measuring the Characteristics of STEM Doctorates

Table 1 presents the distribution of the analytical sample of STEM doctorates by the variables measuring their Ph.D. degree field, demographic characteristics, educational background, and family characteristics. I define STEM fields as including engineering and all mathematical, biological and physical sciences. The field in which each respondent earned his/her degree is coded per a 4-category classification that aggregates the categories of the more detailed major field coding scheme available in the SDR data (Table A1 lists the 4-category aggregation of 15 detailed codes). The biological sciences are the most common fields of specialization among the STEM doctorates, accounting for almost 37 percent of all doctorates, followed by engineering which accounts for about 30 percent and the physical sciences at 22 percent. Math and computer science account for the remaining 11 percent of STEM doctorates. Table 1 reflects the well-documented patterns of sex segregation among STEM fields: women are overrepresented among doctorates in the biological sciences but are underrepresented in all other STEM fields. Women are especially scarce among engineering doctorates where they account for only 18 percent of all doctorates awarded from 1995 to 2013.

This analysis of employment outcomes among STEM doctorates includes controls for age, an indicator of U.S. citizenship, and a 5-category classification of race/ethnicity. Educational background is controlled with two variables: a continuous indicator of the number of years between bachelor's and doctorate degree and a categorical indicator of the Carnegie classification of the doctorates' degree-granting institution. The gender gap in time-to-doctorate may measure an aspect of human capital that is associated with employment outcomes [3], and the influence of the "quality" or prestige of the doctorate-granting institution on the employment outcomes of academic scientists is well-documented [25,26]. Women doctorates take fewer years on average between their bachelor's and doctoral degrees than do men, and although women are not underrepresented among doctorates from R1 universities, they are marginally underrepresented among doctorates from R2 universities. I measure the doctorates' family characteristics with a series of dummy variables indicating the presence of children of aged under 2 years, 2–5 years, and 6–17 years, and a categorical indicator of the presence and employment status of a spouse. Male and female doctorates differ on all the family characteristics measured. Women are less likely than men to be married, more likely to be childless, and more likely to have spouses who work either part or full time.

Table 1. Sample means for variables measuring degree field, demographic characteristics, educational background, and family structure for all recent doctorates, by gender.

	Total	**Males**	**Females**		**% Female**
Sample size (n)	18,687	12,953	5734		30.684
Degree field					
Mathematical & computer sciences	0.113	0.123	0.089	***	24.186
Biological sciences	0.368	0.290	0.544	***	45.316
Physical sciences	0.223	0.237	0.193	***	26.528
Engineering	0.296	0.350	0.175	***	18.092
Demographic characteristics					
Age	33.438 (4.886)	33.552 (4.884)	33.181 (4.881)	***	
U.S. citizen	0.593	0.568	0.650	***	
Race					
White, non-Hispanic	0.574	0.569	0.585	*	
Black, non-Hispanic	0.029	0.026	0.036	***	
Asian or Pacific Islander, non-Hispanic	0.351	0.364	0.324	***	
Hispanic	0.037	0.034	0.044	***	
Other, non-Hispanic	0.008	0.007	0.010		
Educational background					
Years from BA to Ph.D.	9.544 (3.785)	9.617 (3.808)	9.380 (3.727)	***	
Carnegie classification of doctorate-granting institution					
R1 University	0.741	0.744	0.735		
R2 University	0.109	0.111	0.103	†	
Doctorate Granting	0.098	0.099	0.096		
Other	0.052	0.045	0.067	***	
Family Characteristics					
Family structure at time of survey					
No children	0.629	0.604	0.685	***	
Children aged <2 years	0.188	0.200	0.163	***	
Children aged 2–5 years	0.168	0.185	0.130	***	
Children aged 6–17 years	0.122	0.135	0.093	***	
Marital status/Spouse's work status					
Unmarried	0.285	0.274	0.311	***	
Spouse works full time	0.423	0.352	0.581	***	
Spouse works part time	0.073	0.090	0.033	***	
Spouse does not work	0.219	0.283	0.075	***	

Notes: Sample means and standard deviations (in parentheses) are weighted to account for sampling design; † $p \leq 0.10$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$, for two-tailed test of sex differences. Source: Author's calculations using data from the *Survey of Doctorate Recipients* [22], 1995–2013.

2.1.2. Occupation-Level Variables Measuring the Relationship between STEM Fields and Occupations

I create four occupation-level variables to measure occupational sex-typing and the extent to which an occupation is related to a STEM doctorate. See Appendix B for a full discussion of the approach used. The doctorate-occupation relatedness variables aim to quantify the degree to which an occupation requires doctorate-level education, demands research skills, and is substantively related to each degree field. All occupation-level variables are measured using the most detailed level of occupational classification (131 categories) available in the SDR. Table S1 presents the full list of occupational categories, along with the occupational distribution for both the analytical and operational samples of STEM doctorates from the SDR. The occupation-level variables are also allowed, when possible and appropriate, to vary by degree field (using the detailed classification) and survey year. The occupation-level variables are linked to the individual-level data by survey year, occupation, and degree-field.

Demand for Doctoral-Level Education

The variable measuring the occupational requirement for doctoral-level education is generated using data from the O*NET 12.0-18.0 Databases. The O*NET survey asks respondents to specify the level of education, from a list that distinguishes 12 levels of certification and degree attainment, "that is required to perform their job" [24]. I operationalize the demand for doctoral-level education as the percent of O*NET respondents who specify that a doctoral or post-doctoral degree is required for performance of their job. I then aggregate the SOC-level information to the 131-category SDR occupational coding scheme and specify the mean of the percent reporting a requirement for doctoral-level education within the aggregated categories as the measure of occupational demand for doctoral-level education. This variable varies by occupation and year and ranges from 0 to 100.

Occupation-Degree Field Relatedness and Demand for Research Skills

To measure the extent to which occupations are substantively related to degree fields and demand research skills, I use the SDR operationalization cohort data for two survey items that are included in all waves of the SDR survey. The first item reads, "To what extent was your work on your principal job held during the week of [survey reference date] related to your highest degree?" and respondents could choose "closely related," "somewhat related," or "not related." The second survey item is a dichotomous indicator of whether the respondent indicates that "basic research, applied research, development, or design" is either their primary or secondary work activities at their job. The variable measuring occupation-degree relatedness is operationalized as the percent of respondents, identified by each possible combination of the 15-category classification of degree field and the 131-category occupational classification who report that their occupation is "closely related" to their degree field. Similarly, the variable measuring occupational demand for research skills is defined as the percent of respondents identified by each field-occupation pairing who report that research was their primary or secondary work activity. All data are weighted prior to aggregation to account for the sampling design and calculated separately by survey year. The values of both variables range from 0 to 100, and since small cell sizes can produce highly variable estimates with low reliability, each variable is coded to 0 for combinations of degree field and occupation that are experienced by fewer than 5 individuals within each survey year. These variables are linked to the individual-level data by the detailed (15-category) classification of degree field, occupation, and survey year.

Occupational Sex-Typing

I use the percent of females among the operational cohort of doctorates in each of the 131 occupational categories as a measure of the occupational sex-typing.[3] This variable ranges from 0 to 100 and is calculated separately for each year. Including this variable in the analysis allows a test of the degree to which occupational attainment among STEM doctorates at the transition to the labor market follows (or departs from) established patterns of occupational segregation by gender.

2.2. Methods

To analyze gender differences in the labor market outcomes for STEM doctorates, I use regression models for categorical and linear dependent variables. The labor market outcomes that are operationalized as binary variables—labor market entry, full-time work versus less-than-full-time work, and employment at a R1/R2 versus all other postsecondary institutions—are analyzed with binary logit models. The analysis of employment sector, a nominal outcome with 5 categories, uses a multinomial logit. I use linear regression models to analyze gender differences in the doctorate-occupation

[3] To generate reliable measures of the percent female in the observed occupations, I use the full sample of SDR respondents, regardless of degree field. The sample includes 95,244 individuals (57,934 men and 37,310 women).

relatedness variables, occupational percent-female, and salary among the STEM doctorates employed full time.[4] The focal independent variable in all models is FEMALE, an indicator of the doctorates' self-identified gender (FEMALE = 1 for females) and each model includes an extensive set of covariates. The coefficient for FEMALE from each model estimates the average gender gap in labor market outcomes (controlling for all covariates), change over time in the gap, and variation in the gap by STEM field and by family structure.

3. Results

3.1. Gender Differences in the Labor Market Outcomes of STEM Doctorates

Figure 2 presents the probability of each labor force outcome depicted in Figure 1 separately by gender and illustrates how the early post-degree employment outcomes of STEM doctorates differ for women and men. These results address the first two research question: Are there gender differences in the early labor market outcomes of STEM doctorates? For which outcomes are the gender disparities greatest?

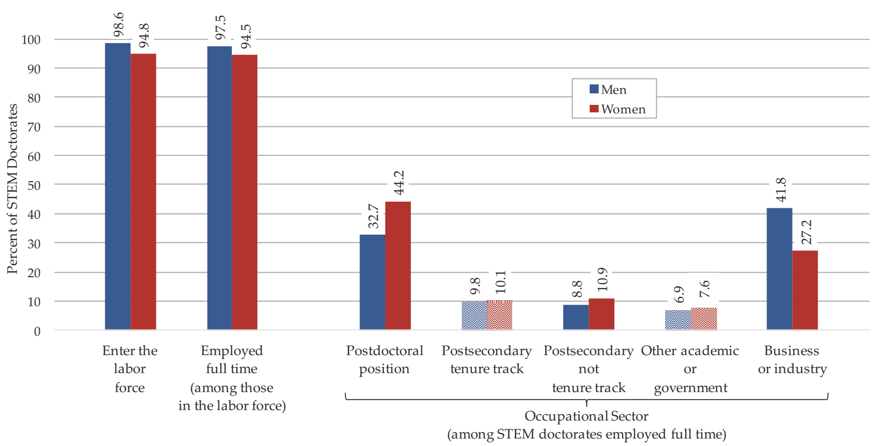

Figure 2. Probability of employment states by gender. *Source*: Author's calculations using data from the *Survey of Doctorate Recipients* [22] and the *O*NET Occupational Information Network Database* [23], 1995–2013. Note: Solid bars represent gender differences that are significant at $\alpha = 0.05$.

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4 The continuous dependent variables that are modeled with linear regressions are logged to correct for the skewness of their distributions. For each employment outcome, I estimate the following general model:

$$Outcome_i = \beta_0 + \beta_1(FEMALE)_i + \beta_2(YEAR)_i + \beta_3(FIELD)_i + \beta_4(FAMILY)_i +$$
$$\beta_5(YEAR \times FEMALE)_i + \beta_6(FIELD \times FEMALE)_i + \beta_6(FAMILY \times FEMALE)_i +$$
$$\varphi_1(EDUC)_i + \varphi_2(EDUC * FEMALE)_i + \varphi_1(X)_i + \varphi_2(X * FEMALE)_i + \varepsilon_{ij}$$

where FEMALE is an indicator of the doctorates' self-identified gender (FEMALE = 1 for females), YEAR represents both the linear and quadratic specification for survey year (which also distinguishes each cohort of doctorates), FIELD represents the categorical indicator of the doctorates' STEM degree field, FAMILY represents the variables measuring family structure, EDUC represents the measures of educational background, and X is a vector of control variables measuring the doctorates' demographic characteristics and other covariates specifically relevant to each outcome. The models of salary and occupational characteristics (demand for doctoral degree, occupation-degree field relatedness, demand for research skills, and percent female in the occupation) include controls for hours worked, employment sector, and all the other occupational characteristics. Percent female in the occupation is not included as a control variable in the occupational characteristic models because it is very highly correlated with both the other outcome variables and the covariates. Including percent female obscures the estimated association between doctorate gender and the other occupational characteristics that are correlated with percent female. The regression model of occupational percent female, however, includes all occupational characteristic variables as covariates.

The probability of labor force participation is very high for all doctorates, but women are less likely than men to enter the labor force. Full-time employment is the norm among the STEM doctorates who enter the labor force, but women are slightly less likely than men to work full time hours. Entering a postdoctoral position or a job in business or industry are the most likely post-degree transitions for the doctorates who work full-time but there are significant gender differences in these paths. Women are significantly more likely to enter postdoctoral positions: 44.2 percent of women but only 32.7 percent of men are in postdoctoral positions 2 years after attaining their degree. In contrast, entering business or industry is much more common for men than it is for women. About 42 percent all male doctorates who enter full-time employment within two years of obtaining their doctorate do so in business or industry, compared to only 27.2 percent of women. Entering faculty positions is much less common for STEM doctorates. Ten percent of both women and men enter tenure-track faculty positions in postsecondary institutions. Another 10 percent enter non-tenure-track faculty positions and women are slightly overrepresented among the doctorates in such positions. Entry into "other academic or government" jobs is a path taken by only 7 percent of STEM doctorates and is equally likely for men and women.

Figure 3 presents descriptive statistics for the occupational characteristics relevant to each employment sector the STEM doctorates may enter. Among the doctorates who enter either a postdoctoral or a tenure-track faculty position (panel a of Figure 3), women are less likely than men to attain such positions at research-intensive universities. Panel (b) of Figure 3 shows that there also are gender differences on all four measures of the characteristics of occupations outside of the normative Ph.D.-to-faculty career path. Among the doctorates who enter non-tenure-track postsecondary positions, other academic or government jobs, or business and industry, women are more likely than men to enter occupations that require doctoral-level education and that are closely related to their degree fields. However, the occupations women enter are less likely to primarily focus on research than those occupations entered by men. The significant gender gap in the mean percent female in the occupations entered by men (23.6) and women (33.0) testifies to the prevalence of occupational sex segregation among the STEM doctorates who leave the tenure-track career trajectory: women tend to enter occupations with a greater representation of women than do the male members of their doctoral cohorts. Finally, there is a significant gender gap in earnings among all STEM doctorates who are employed full time. Within two years of earning their degree, women with a STEM doctorate who are employed full time earn, on average, $12,400 less per year than their male colleagues.

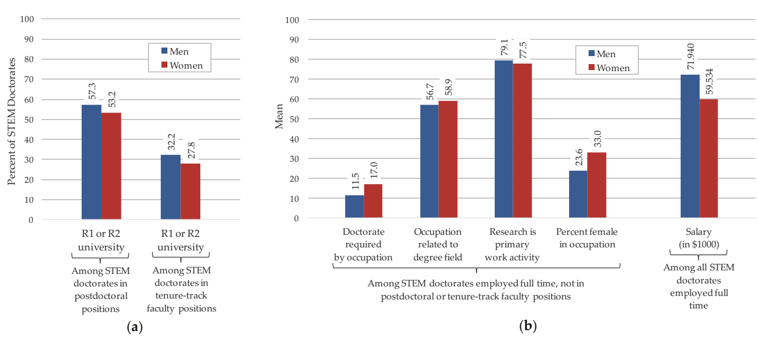

Figure 3. Gender-specific means for the variables measuring the characteristics of occupations entered by STEM doctorates who are employed full time: (**a**) the percent of STEM doctorates who attain postdoctoral or tenure-track faculty positions at R1 or R2 universities; and (**b**) salary, and the degree to which an occupation requires doctorate-level education, is closely related the doctorate's degree field, demands research skills, and is female-dominated. *Source*: Author's calculations using data from the *Survey of Doctorate Recipients* [22] and the *O*NET Occupational Information Network Database* [23], 1995–2013. Note: All gender differences are significant at $\alpha = 0.05$.

3.2. Have the Gender Differences in Early Labor Market Outcomes among STEM Doctorates Changed over Time?

Results from the multivariate model of each labor market outcome are presented in Figures 4–6. These figures summarize the statistical results relevant to the research questions that motivate this analysis: Have the observed gender differences in the early labor market outcomes of STEM doctorates changed over time?

The results are presented using the estimated marginal effect of FEMALE from the multivariate models for each labor market outcome. The full set of coefficients for each multivariate model are presented in Tables A2–A5. Marginal effects are useful for interpreting the results of both linear and nonlinear models, but they are particularly helpful for the interpretation of estimates from models that include many interaction terms such as those used in this analysis [27]. The figures present the average marginal effect of FEMALE, i.e., the gender gap for the "average" STEM doctorate (when all covariates are set to their mean value), and the 95% confidence interval for the marginal effect, by year. Negative values of the marginal effect indicate a female deficit in the likelihood of an outcome. If the gender gap in an employment outcome has changed significantly over time the heights of the bars will differ such that the confidence intervals do not overlap.

Figure 4 presents the trends in the estimated gender gap in the rates of labor force participation among all STEM doctorates, and of full-time employment among the doctorates who enter the labor force. These results show that, controlling for the doctorates' educational background and family structure, women are about 3 percent less likely than men to enter the labor force, and the magnitude of the gender gap is unchanged across all 9 cohorts included in this analysis. Among the doctorates who do enter the labor force, women are about 2 percent less likely than men to work full-time, although this small gender gap may have closed as it is not significant for the most recent cohort.

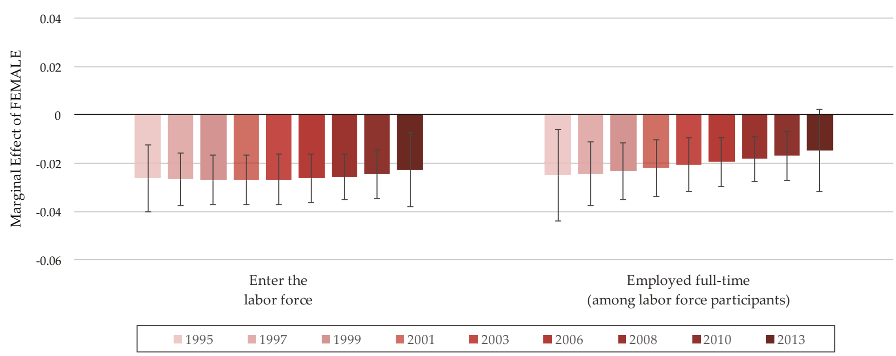

Figure 4. Estimated marginal effects of FEMALE on the likelihood of labor force participation and full-time employment (among those in the labor force), for all STEM doctorates by year. *Source*: Author's calculations using data from the *Survey of Doctorate Recipients* [22] and the *O*NET Occupational Information Network Database* [23], 1995–2013.

Figure 5 presents the cohort-specific gender gaps in the likelihood of each employment sector outcome among full-time employed doctorates. These results identify the significant gender differences in the post-degree career paths of STEM doctorates and how these disparities have changed over time. Among the cohorts of doctorates who earned their degrees in the late 1990s, women were significantly more likely than men to enter postdoctoral positions and less likely to take jobs in business or industry. However, the gender gap in postdoc entry declined and then reversed, and the gap in entering business or industry declined to insignificance—among the 2010 and 2013 cohorts, women are significantly less likely than men to enter postdocs, and there is no gender gap in the likelihood that a STEM doctorate will take a job in business or industry. In contrast, the estimates indicate that there is a growing female advantage in the likelihood that a doctorate attains a tenure-track faculty position. Starting with the cohorts who earned their degrees in the early 2000s, the probability that a STEM doctorate enters a tenure-track faculty position has been 2 to 4 percent greater for women than men. In addition, contrary to the expectation that women have been marginalized in non-tenure-track positions more often than men, the results indicate that a female advantage in the likelihood of entering a non-tenure-track faculty position emerged only for the most recent cohorts, while there was gender parity in this employment outcome for the 1995–2008 cohorts.

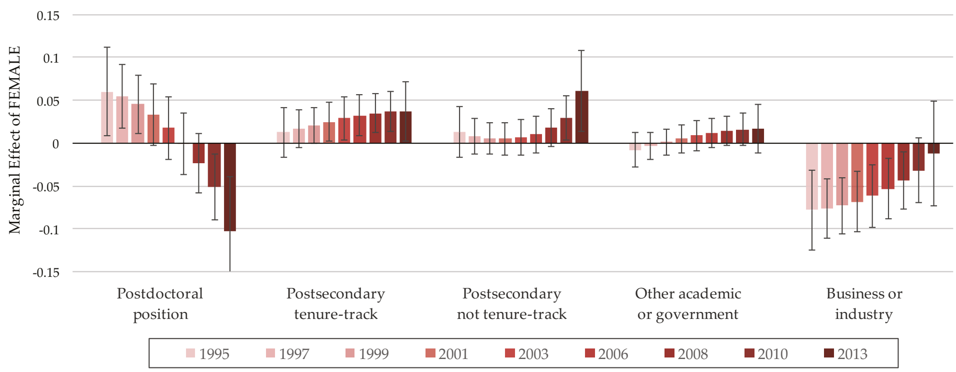

Figure 5. Estimated year-specific marginal effects of FEMALE on employment sector outcome among all STEM doctorates employed full time. *Source*: Author's calculations using data from the *Survey of Doctorate Recipients* [22] and the *O*NET Occupational Information Network Database* [23], 1995–2013.

Figure 6 presents the estimated gender gaps in the characteristics of the occupations entered by STEM doctorates, controlling for the doctorates' educational and family characteristics. The results presented in panel (a) show that among the doctorates who entered postdoctoral or tenure-track faculty positions directly after completing their degree, women and men in all cohorts are equally likely to attain such positions at R1 or R2 universities. There are, however, gender gaps in the characteristics of the jobs attained by doctorates who gain employment in the non-tenure-track postsecondary, other academic or government, or business and industry sectors (panel b). Women are more likely than men to enter jobs that require doctoral-level education, although this gender gap was largest among the 1990s cohorts and has declined across the cohorts. Women and men from all cohorts have been equally likely to utilize their educational investments by entering jobs that are closely related to their degree fields, but women in the 1999-2008 cohorts were less likely to attain research-focused jobs. The significantly positive marginal effects of FEMALE for the percent female in an occupation reflect a significant level of occupational segregation among the STEM doctorates when they first enter the labor market: they show that women are more likely than men to enter jobs with a higher relative representation of women, while men are more likely to enter jobs where men predominate. This tendency toward occupational sex segregation appears to have declined across the cohorts, but remains statistically significant. In addition, the results in panel (c) show that a significant gender gap in earnings emerges at the very start of the STEM doctorates' employment and that this gender gap has changed little across the cohorts. The model estimates indicate that women STEM doctorates start their careers earning 4 to 7 percent less than men with the same employment sector, job characteristics, educational credentials and family characteristics.

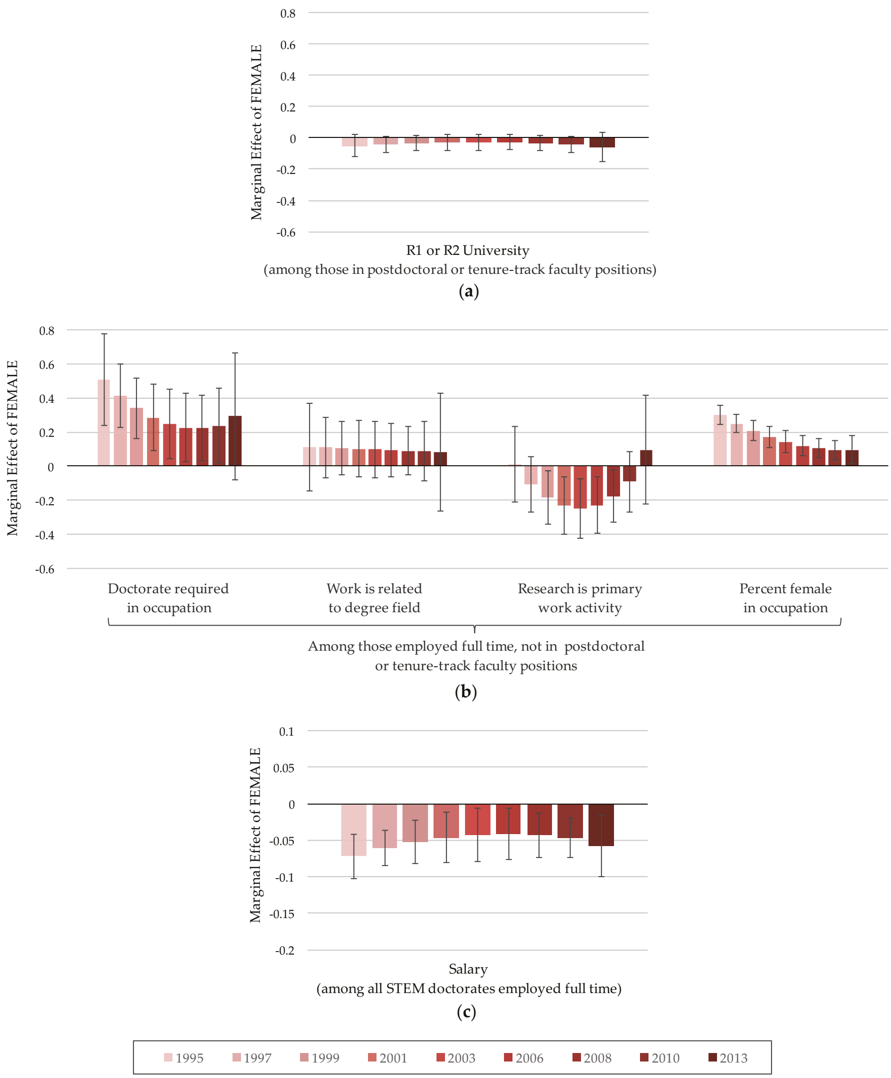

Figure 6. Average estimated marginal effects of FEMALE on the likelihood of: (**a**) employment at a R1 or R2 university (among STEM doctorates entering postdoctoral or tenure-track faculty positions); (**b**) employment in an occupation that requires a doctoral degree, that is related to a doctorate's degree field, in which research is the primary work activity, and that is female-dominated (among STEM doctorates employed in non-tenure-track positions, other academic and government positions, or in business or industry); and (**c**) salary among all STEM doctorates employed full-time. *Source*: Author's calculations using data from the *Survey of Doctorate Recipients* [22] and the *O*NET Occupational Information Network Database* [23], 1995–2013.

3.3. Do the Gender Differences in Labor Market Outcomes Vary by STEM Field or Family Characteristics?

The aggregate gender differences in the labor market outcomes of STEM doctorates described above may mask differences across STEM fields or by the family characteristics of the scientists. The patterns may vary across field because of differences in normative career paths and employment opportunities, or because of field-specific differences in the representation of women and the experience of bias or discrimination. Similarly, the aggregate gender gaps may not reflect the experience of all scientists but may instead be driven by a distinct subgroup such as those who have young children or are in dual-earner couples. The multivariate analyses test if the aggregate patterns are representative or if specific populations drive them. The results may inform our understanding of the causes of the observed gender disparities and guide interventions aimed at reducing them.

To test if the gender differences in labor market outcomes vary by STEM field or family characteristics, I estimate the marginal effect of FEMALE, i.e., the estimated gender gap, for each of the labor market outcomes separately by degree field, parental status and marital status (controlling for all other covariates). Tables 2 and 3 present the results. In addition, I estimate the marginal effects of FEMALE for job characteristics and salary separately by employment sector to provide additional information about the labor force contexts where gender disparities are most significant. Negative values that are statistically significant indicate a female deficit in the likelihood of an outcome. All estimates control for the doctorates' individual demographics, educational credentials, family characteristics, and employment characteristics (see Tables A2–A5 for the full model specifications). In Tables 2 and 3, the statistical significance of *within-group* gender differences, e.g., the gender gap among engineering doctorates, is indicated by stars, and significant *between-group* differences (α = 0.05) in the magnitude of the gender gaps, i.e., between the four degree fields or family types, are indicated by bolded text. The focus of this part of the analysis is on the significance of between-group differences (bold values) since these indicate that a covariate is associated with gender disparities in an employment outcome and may therefore help to explain the overall gender gaps in the career trajectories of STEM doctorates.

Table 2. Estimated marginal effect of FEMALE on labor force entry, full-time employment, and employment sector, by degree field and family characteristics

	Among all STEM doctorates	Among those who enter the labor force	Among all STEM doctorates employed full time				
	Labor force entry	**Full time employment**	**Post-doctoral position**	**Post-secondary, tenure track**	**Post-secondary, *not* tenure track**	**Other academic or gov't**	**Business or industry**
Average	–0.027 ***	–0.034 ***	0.016	0.029 *	0.007	0.009	–0.061 ***
Panel A: Degree field							
Mathematical & computer sci.	–0.018 **	–0.041 **	**–0.024**	**0.075** *	0.034	0.001	**–0.087** **
Biological sciences	–0.018 *	–0.012 *	**0.044** *	**–0.009**	–0.018	0.004	**–0.022**
Physical, chemical & earth sci.	–0.026 ***	–0.017 *	**–0.057** *	**0.046** **	0.028 *	0.022 †	**–0.039**
Engineering	–0.036 ***	–0.028 ***	**0.040** *	**0.069** ***	0.009	0.009	**–0.127** ***
Panel B: Family Characteristics							
Family structure at time of survey							
No children	**–0.016** ***	**–0.010** *	–0.002	0.025	0.008	0.010	–0.041 *
Children aged <2 years	**–0.092** ***	**–0.069** ***	0.050 †	0.040	–0.028	0.023	–0.085 **
Children aged 2–5 years	**–0.050** ***	**–0.057** ***	0.026	0.049 *	0.034 †	–0.005	–0.104 ***
Children aged 6–17 years	**–0.030** ***	**–0.025** **	0.063 †	0.017	0.018	–0.001	–0.096 *
Marital status/Spouse's work status							
Unmarried	**–0.020** **	**–0.005**	–0.005	0.031 *	–0.007	0.013	–0.032
Spouse works full time	**–0.044** ***	**–0.040** ***	0.007	0.025	0.022 †	0.008	–0.061 **
Spouse works part time	**–0.040** *	**–0.045** *	0.002	0.079	–0.024	–0.029	–0.028
Spouse does not work	**–0.010**	**–0.008**	0.059 †	0.023	0.007	0.022	–0.110 **

Note: Marginal effects are estimated based on the full regression models of employment outcomes; see Tables A2 and A3 for model specifications and estimated coefficients. Statistical significance of individual marginal effects of FEMALE is indicated by stars: † $p \leq 0.10$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$. Statistically significant (α = 0.05) between-group differences, e.g., between the categories of degree field, in the estimated marginal effect of FEMALE are indicated by bold text. Source: Author's calculations using data from the *Survey of Doctorate Recipients* [22] and the *O*NET Occupational Information Network Database* [23], 1995–2013.

3.3.1. STEM Degree Field

The marginal effects of FEMALE by degree field for each employment outcome are presented in Panel A of Tables 2 and 3. These results show that gender disparities in labor force participation and attachment, in most job characteristics and in salary do not vary by STEM field, but that gender differences in employment sector do vary by field. A greater proportion of women than men enter postdoctoral positions among doctorates in the biological sciences and engineering, but the gender gap is reversed among doctorates in the physical sciences, where men are more likely than women to enter postdocs. The female advantage in attaining tenure-track faculty positions is observed among doctorates in the mathematical and computer sciences, physical sciences, and engineering, but not among biological science doctorates. In addition, the female deficit in the likelihood of taking a job in business or industry is large and significant only among doctorates in engineering and the mathematical and computer sciences. In short, the aggregate pattern of gender differences in the employment sector outcomes (shown in Figure 2 above) appears to be driven by the gender differences among doctorates in engineering and the mathematical and computer sciences. In these fields, which are the most male-dominated of the STEM fields, women are overrepresented among the doctorates who pursue the traditional academic career path by entering a postdoctoral or faculty position, and men are overrepresented among those who enter business or industry. In contrast, there are few gender disparities in the employment outcomes of doctorates in the biological sciences, the most gender balanced field.

Table 3. Estimated marginal effect of FEMALE on job characteristics and salary, by degree field and family characteristics.

	Among postdocs & tenure-track faculty	Among STEM doctorates employed full time, not in postdoctoral or tenure-track positions				Among all STEM doctorates employed full time
	R1 or R2 University	Doctorate required in occupation	Work is related to degree field	Research is primary work activity	Percent female in occupation	Salary
Average	–0.058 ***	0.244 *	0.097	–0.247 **	0.137 ***	–0.046 *
Panel A: Degree field						
Mathematical & computer sci.	–0.028	**0.200**	0.182	–0.495 **	0.115 *	–0.028
Biological sciences	–0.010	**0.034**	0.014	0.024	0.058	–0.047 *
Physical, chemical and earth sci.	–0.035	**–0.074**	0.377 *	–0.310 *	0.185 ***	–0.068 *
Engineering	–0.068	**0.539** ***	–0.019	–0.302 *	0.165 **	–0.032
Panel B: Family Characteristics						
Family structure at time of survey						
No children	–0.039	0.274 *	0.094	–0.243 **	0.143 ***	–0.053 **
Children aged <2 years	–0.017	0.157	0.308 †	–0.181	0.070	–0.023
Children aged 2–5 years	–0.038	0.214	–0.121	–0.135	0.152 ***	–0.027
Children aged 6–17 years	0.032	0.222	0.107	–0.512 **	0.174 **	–0.056 †
Marital status/Spouse's work status						
Unmarried	–0.037	0.362 *	0.051	–0.116	0.141 ***	–0.008
Spouse works full time	–0.005	0.168	0.144	–0.233	0.145 ***	–0.030
Spouse works part time	–0.005	0.713 **	0.046	–0.072	0.155 *	–0.118 **
Spouse does not work	–0.074	0.101	0.088	–0.455 **	0.114	–0.086 **
Panel C: Employment sector						
Postdoctoral position	–0.021					–0.012
Postsecondary, tenure track	–0.040					–0.057 *
Postsecondary, not tenure track		–0.177	0.072	**–0.228**	0.134 **	–0.033
Other academic or government		–0.003	0.194	**–0.195**	0.198 ***	–0.088 **
Business or industry		0.396 ***	0.085	**–0.262** **	0.126 **	–0.057 *

Note: Marginal effects are estimated based on the full regression models of employment outcomes; see Tables A4 and A5 for model specifications and estimated coefficients. Statistical significance of individual marginal effects of FEMALE is indicated by stars: † $p \leq 0.10$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$. Statistically significant ($\alpha = 0.05$) between-group differences, e.g., between the categories of degree field, in the estimated marginal effect of FEMALE are indicated by bold text. Source: Author's calculations using data from the *Survey of Doctorate Recipients* [22] and the *O*NET Occupational Information Network Database* [23], 1995–2013.

The estimates presented in Panel A of Table 3 show that the gender differences in the types of jobs the doctorates attain generally do not vary significantly across degree field. Among the doctorates that enter postdoctoral positions or tenure-track faculty jobs, women and men from all degree fields are equally likely to attain these positions at research-intensive universities. For the doctorates that do not enter postdocs or tenure-track faculty positions, there are gender differences in the types of jobs they attain but, with only one exception, the between-field disparities do not attain statistical significance. The aggregate female advantage in the likelihood that a doctorate attains a job that requires Ph.D.-level education is driven by those in engineering fields. Women and men are, on average, equally likely to attain jobs that are related to their degree field, although women with physical science doctorates are more likely than men to utilize their field-specific education on the job. In contrast, the female deficits in the attainment of research-oriented jobs and the tendency toward occupation sorting by sex are significant for doctorates in all degree fields, *except* the biological sciences. Yet, the biological sciences and the physical sciences are the two fields in which women doctorates earn significantly less than men even when they have equivalent background and employment characteristics.

The estimated marginal effects of FEMALE presented in Panel C of Table 3 provide additional information about the labor market contexts in which these occupational gender disparities occur. Both the female advantage in attainment of jobs that require a doctoral degree and the female disadvantage in the attainment of research jobs are concentrated among those who enter business or industry jobs. The tendency for doctorates to segregate into gender-typed occupations, however, is universal across the non-tenure-track postsecondary, other academic and government, and business and industry sectors. The gender gap in salary is also universal across sectors, although it reaches statistical significance only among doctorates who enter tenure-track faculty positions, other academic or government jobs, and positions in business or industry.

3.3.2. Family Structure

The estimated gender disparities in labor force entry, full-time work and employment sector by the measures of family structure are presented in Panel B of Tables 2 and 3. These estimates show that gender differences in labor force participation and the likelihood of working full time are strongly associated with the STEM doctorates' family characteristics but that subsequent employment outcomes are not. The female deficit in labor force participation is significant for all family structures but it is greatest among doctorates with young children (aged less than 2 years) and those in dual-earner marriages (doctorates' whose spouses work either full or part time), indicating that gender differences in the influence of the household division of labor, especially as it relates to childbearing and caring for young children, is a significant cause of the gender gap in labor force participation among STEM doctorates. The gender gap in the likelihood of full-time employment is also strongly associated with the parenting of young children and dual-career marital status. Among doctorates who have no children, the rate of full-time employment is one percent lower for women than men, but for doctorates with young children, the likelihood of full-time employment is 5–9 percent lower for women than men. Similarly, there is no gender gap in the likelihood of full-time employment among unmarried doctorates and doctorates whose spouses do not work, but the gender gap increases to 4 percent among doctorates who have spouses who work either full or part time.

The estimated gender differences in the doctorates' employment sector outcomes, the characteristics of the jobs they attain and the salaries they earn are presented in Panel B of Table 3. These results show that the aggregate pattern of gender differences in these employment outcomes do not vary by the doctorates' family status, so the gender gaps in these labor force outcomes cannot be explained by gender differences in the distribution or influence of family characteristics. Notably, this analysis provides no evidence that marital or parental status affects the female advantage in the likelihood of employment in tenure-track faculty positions or the female deficit in the likelihood of employment in business or industry. Nor do family characteristics appear to affect gender differences in the types of jobs doctorates attain, their salary, or the tendency for doctorates to enter sex-typed occupations. In fact, after controlling for all covariates, the gender gap in salary is significant only for doctorates who are childless, for whom there can be no effect of parenthood, and those who have spouses who work part-time or not at all, for whom dual-career conflicts should be minimal.

4. Discussion

This analysis provides some insight into the gender disparities that characterize the transition of STEM doctorates to the labor market and that may affect their subsequent career trajectories. The time frame of this analysis is narrow—the 2 years following the doctorate's degree attainment—so the parities and disparities identified are not necessarily representative of later career outcomes since they have yet to be affected by any significant exposure to labor market influences. They are consequential, however, since early career transitions and achievements may at least condition, if not determine, subsequent opportunities and outcomes.

Among the nine cohorts of STEM doctorates who earned their degrees between 1995 and 2013, I find that women are less likely than men to enter the labor force and work full-time, and that these disparities are consistent across STEM fields and have changed only slightly across the cohorts. I also find significant gender differences in the types of employment attained by STEM doctorates and some of these results contradict long-held perceptions of gender disparities in the STEM labor market. The results indicate that among the early cohorts of doctorates, women were more likely than men to enter postdoctoral positions but that the gender gap declined and then reversed so that men are now overrepresented among the doctorates entering postdoctoral positions. The gender gap in entry into postdoctoral positions varies by STEM field so the stark aggregate trend may reflect field-specific changes in the availability and career necessity of postdocs, as much as it may reflect changes in the behavior of men and women: while postdoctoral positions have long been a normative part of the career trajectory in the female-dominated biological sciences, over time they are increasingly available and a required precursor to faculty positions in the male dominate STEM fields.

In contrast to prior studies, I find that women are more likely than men to enter tenure-track faculty positions within two years of completing their doctorate and that they are as likely as men to obtain these positions at research-intensive universities. I also find that the overrepresentation of women among doctorates who attain non-tenure-track academic positions emerged only among the most recent cohorts, when the availability of such positions increased significantly. The discrepancy between the results reported here and the existing literature may be attributed to differences in research design, and they thereby highlight the need for carefully constructed analyses. This study explicitly parses gender disparities in labor force participation and attachment from employment outcomes whereas prior analyses often conflate these, and thereby overestimate the gender gap in attainment of faculty positions, by simply comparing the representation of women among tenure-track assistant professors to that among recent cohorts of doctorates without additional controls. Furthermore, by focusing on a narrow post-degree period, the results of this analysis likely understate the gender differences that ultimately develop among each cohort of doctorates, but they more accurately indicate that those disparities develop at later points in the career trajectory. These points underscore the necessity of disaggregating employment transitions to the most detailed level possible to accurately identify the processes that drive gender differences in career trajectories. By looking at narrow slices of the career trajectories and explicitly examining how they are connected, we can more accurately identify where the disparities are occurring, what are their causes, and we therefore will be better able to develop policies that will generate greater gender equity in STEM career development.

By using an inclusive conceptualization of employment outcomes that includes and attempts to disaggregate non-academic career tracks, this analysis provides a more comprehensive and nuanced picture of gender differences in the career paths of STEM doctorates and in the likelihood they will "leave" science. The results show that women are less likely than men to gain employment in business and industry and that this gender disparity is greatest among doctorates in engineering and the mathematical and computer sciences, but that it may have declined over time. Among the doctorates who enter business or industry, the alternative approach to identifying who "stays in the pipeline" developed for this analysis shows that women are more likely than men to enter jobs that require a doctorate, and they are at least as likely as men to enter occupations that are related to their degree field. However, I also find that women in all fields, except the biological sciences, are significantly less likely than men to enter research-oriented jobs. Therefore, women may persist in STEM but are "lost" from research jobs. The gender-specific patterns of education-occupation matching identified in this analysis reflect processes of gender sorting across a range of occupational characteristics that has been under-appreciated and warrant further investigation. A more well-known pattern that this analysis clearly identifies as a persistent influence on the occupational attainment of doctorates, is occupational segregation by sex. In addition, while the results of this analysis suggest that the extent to which STEM doctorates enter gender-segregated occupations has declined over time, it remains significant among the most recent cohorts and in all STEM fields except the biological sciences.

The results of this analysis echo the refrain of the growing body of the gender and work literature: family structure has a negative impact on the employment outcomes of women in the STEM fields. However, this study joins the chorus in a limited way: I find that the presence of children and the gendered impact of being in a dual-earner couple are strong negative influences on the early employment outcomes of women, but *only* because they disproportionately inhibit their labor market entry and full-time labor force attachment. Gender differences in other dimensions of the transition into the labor market are not influenced as strongly by marital or parental status, nor is there evidence that the female-specific influence of the presence of young children or a working spouse are driving either the differential sorting of men and women across employment sectors and occupations, or the significant gender gap in earnings.

Overall, these results indicate that there has been some progress toward gender equity at the earliest stages of the career trajectories of STEM doctorates but that this progress is slow and variable across STEM fields. In general, the greatest gender gaps remain in those fields where women's representation continues to lag, but disparities in outcomes persist even when gender parity in representation is approached. Further analysis of the labor market processes and outcomes that follow the initial transitions investigated here should assess if similar progress toward equity is being attained and how the gender disparities vary by race/ethnicity and other social identities. The experiences of STEM doctorates who enter jobs in business and industry is an area that is particularly in need of both data collection and analysis. Although an increasing number of STEM doctorates enter business and industry, there are few data sources that can adequately inform our understanding of their labor market experiences and outcomes, or the forces that influence the significant gender disparities in that sector which this analysis identified.

Supplementary Materials: The following are available online at www.mdpi.com/2076-0760/6/1/24/s1, Table S1: Percent distribution by occupational category, for analytical and operational samples, separately by gender and degree field.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. Percent distribution of analytical and operational samples by degree field and gender.

	Sample of Recent Doctorates					Operational Sample of Doctorates				
	Total	Males	Females		%Female	Total	Males	Females		%Female
Sample size (n)	18,687	12,953	5734		30.68	63,962	47,700	16,262		25.42
Degree field										
Math & computer sciences										
Computer & information sciences	5.25	6.09	3.37	***	19.68	4.61	5.12	3.11	***	17.15
Mathematics & statistics	6.00	6.22	5.50	†	28.13	5.57	5.80	4.91	***	22.40
Agricultural & food sciences	2.95	2.79	3.31	†	34.45	3.58	3.56	3.62		25.76
Biological sciences										
Biochemistry & biophysics	5.24	4.65	6.59	***	38.57	1.54	1.33	2.16	***	35.70
Cell & molecular biology	5.89	4.33	9.41	***	49.06	1.75	1.52	2.43	***	35.33
Microbiology	2.60	1.86	4.27	***	50.40	0.72	0.35	1.81	***	63.87
Other biological sciences	20.14	15.42	30.79	***	46.91	29.86	23.87	47.44	***	40.40
Physical sciences										
Chemistry, except biochemistry	11.11	10.77	11.87	*	32.80	12.17	12.04	12.53		26.19
Earth, atmospheric & ocean sciences	3.34	3.34	3.34		30.68	3.32	3.41	3.08	*	23.59
Physics, astronomy & astrophysics	7.88	9.56	4.09	***	15.94	8.38	9.67	4.58	***	13.90
Engineering										
Chemical engineering	3.39	3.79	2.47	***	22.34	3.39	3.80	2.18	***	16.38
Civil engineering	2.55	3.00	1.55	***	18.63	2.38	2.82	1.08	***	11.58
Electrical & computer engineering	8.80	10.85	4.17	***	14.54	8.49	10.25	3.33	***	9.95
Materials, metallurgical & mechanical	7.41	9.06	3.69	***	15.28	5.18	6.25	2.01	***	9.89
Other engineering	7.45	8.28	5.58	***	22.97	9.07	10.22	5.71	***	16.01

Note: † $p \leq 0.10$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$, for two-tailed test of sex differences. Source: Author's calculations using data from the *Survey of Doctorate Recipients* [22], 1995–2013.

Table A2. Estimated coefficients from logit models of labor force entry and employment vs. post-doctoral position.

	Labor force entry						**Full-time vs. Part-time Employment**					
	Main effect			***FEMALE**			**Main effect**			***FEMALE**		
	b	**se(*b*)**		***b***	**se(*b*)**		***b***	**se(*b*)**		***b***	**se(*b*)**	
Constant	0.077	(2.991)					8.150	(1.866)	***			
Female	1.958	(0.954)	*				–0.972	(0.805)				
Year	0.032	(0.061)		–0.034	(0.081)		0.123	(0.049)	*	–0.050	(0.069)	
Year^2	–0.001	(0.003)		0.002	(0.005)		–0.005	(0.003)	†	0.003	(0.004)	
Demographic characteristics												
Age	0.141	(0.182)					–0.224	(0.112)	*			
Age^2	–0.001	(0.002)					0.002	(0.001)				
U.S. citizen	–0.159	(0.151)					–0.288	(0.135)	*			
Race (reference = White, non-Hispanic)												
Black, non-Hispanic	0.125	(0.262)					–0.343	(0.179)	†			
Asian or Pacific Islander, non-Hispanic	–0.312	(0.153)	*				0.130	(0.147)				
Hispanic	–0.105	(0.219)					–0.007	(0.200)				
Other, non-Hispanic	–0.590	(0.427)					–0.270	(0.347)				
Degree field (reference = Mathematical & computer sciences)												
Biological sciences	–1.211	(0.334)	***	0.730	(0.425)	†	0.273	(0.204)		0.519	(0.284)	†
Physical sciences	0.079	(0.393)		–0.344	(0.494)		0.040	(0.207)		0.454	(0.306)	
Engineering	0.163	(0.376)		–0.708	(0.480)		0.611	(0.206)	**	–0.135	(0.315)	
Educational background												
Years from BA to Ph.D.	0.258	(0.140)	†	–0.412	(0.161)	*	0.036	(0.109)		0.162	(0.128)	
Years from BA to Ph.D.2	–0.013	(0.006)	*	0.018	(0.007)	**	–0.002	(0.004)		–0.004	(0.005)	
Carnegie classification of doctorate-granting institution (reference = Research University I)												
Research University II	0.120	(0.318)		–0.501	(0.370)		0.094	(0.219)		–0.444	(0.297)	
Doctorate Granting I & II	0.042	(0.350)		0.215	(0.443)		–0.521	(0.190)	**	0.475	(0.286)	†
Other	–0.113	(0.291)		0.255	(0.413)		0.366	(0.354)		–0.296	(0.460)	
Family Characteristics												
Family structure at time of survey (reference = No children)												
Children aged <2 years	–0.154	(0.262)		–1.217	(0.303)	***	–0.226	(0.189)		–0.876	(0.245)	***
Children aged 2–5 years	0.161	(0.278)		–0.755	(0.325)	*	–0.099	(0.187)		–0.757	(0.245)	**
Children aged 6–17 years	0.395	(0.362)		–0.420	(0.421)		0.469	(0.213)	*	–0.420	(0.290)	
Marital status/Spouse's work status (reference = Unmarried)												
Spouse works full time	0.303	(0.208)		–0.809	(0.284)	**	0.372	(0.175)	*	–1.065	(0.251)	***
Spouse works part time	0.832	(0.443)	†	–1.178	(0.612)	†	0.659	(0.260)	*	–1.365	(0.426)	***
Spouse does not work	0.557	(0.307)	†	0.116	(0.496)		0.462	(0.201)	*	–0.236	(0.420)	
Model goodness-of-fit statistics												
Sample (n)	18,687						17,831					
Wald $\chi 2$ (df)	476.02 (40)						440.09 (40)					
Pseudo R2	0.123						0.088					

Note: † $p \leq 0.10$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$, for two-tailed test of sex differences. Source: Author's calculations using data from the *Survey of Doctorate Recipients* [22] and the *O*NET Occupational Information Network Database* [23], 1995–2013.

Table A3. Estimated coefficients from multinomial logit models of employment sector.

	Reference Category = Business or Industry															
	Postdoctoral Position				Faculty Position, Tenure Track				Faculty Position, Not Tenure Track				Other Academic or Government			
	Main Effect		* Female		Main Effect		* Female		Main Effect		* Female		Main Effect		* Female	
	b	**se(*b*)**	***b***	**se(*b*)**	***b***	**se(*b*)**	***b***	**se(*b*)**	***b***	**se(*b*)**	***b***	**se(*b*)**	***b***	**se(*b*)**	***b***	**se(*b*)**
Constant	−0.619	(0.165)			−1.826	(1.441)			−3.740	(1.521) *			−8.365	(1.666) ***		
Female	0.740	(0.447) †			−0.028	(0.578)			−0.132	(0.605)			0.269	(0.678)		
Year	−0.065	(0.021) **	−0.002	(0.038)	0.041	(0.031)	0.005	(0.058)	−0.026	(0.032)	−0.041	(0.056)	−0.005	(0.033)	0.037	(0.060)
Year^2	0.005	(0.001) ***	−0.002	(0.002)	−0.002	(0.002)	0.000	(0.003)	0.003	(0.002) †	0.002	(0.003)	0.000	(0.002)	−0.001	(0.003)
Demographic characteristics																
Age	−0.007	(0.071)			0.022	(0.087)			0.083	(0.090)			0.253	(0.098) **		
Age^2	0.000	(0.001)			0.000	(0.001)			0.000	(0.001)			−0.003	(0.001) *		
U.S. citizen	−0.385	(0.062) ***			0.360	(0.083) ***			0.216	(0.092) *			1.024	(0.110) ***		
Race (reference = White, non-Hispanic)																
Black, non−Hispanic	−0.214	(0.120) †			0.224	(0.136)			0.249	(0.138) †			0.363	(0.150) *		
Asian or Pacific Islander, non-Hisp.	−0.213	(0.063) ***			−0.710	(0.091) ***			−0.426	(0.099) ***			−0.585	(0.113) ***		
Hispanic	0.061	(0.101)			0.062	(0.127)			−0.013	(0.132)			0.079	(0.140)		
Other, non-Hispanic	0.081	(0.227)			−0.094	(0.343)			0.310	(0.324)			0.554	(0.255) *		
Degree field (reference = Mathematical & computer sciences)																
Biological sciences	2.089	(0.107) ***	0.129	(0.196)	−0.560	(0.119) ***	−0.491	(0.205) *	0.310	(0.324)	−0.132	(0.605)	0.554	(0.255) *	0.269	(0.678)
Physical sciences	1.109	(0.104) ***	−0.100	(0.203)	−1.222	(0.118) ***	0.143	(0.213)	0.836	(0.130) ***	−0.597	(0.221) **	0.815	(0.169) ***	−0.047	(0.305)
Engineering	−0.521	(0.105) ***	0.414	(0.212) †	−1.450	(0.104) ***	0.306	(0.200)	−0.186	(0.140)	−0.093	(0.243)	0.326	(0.169) †	0.166	(0.316)
Educational background																
Years from BA to Ph.D.	0.169	(0.051) ***	−0.139	(0.073) †	0.055	(0.068)	0.032	(0.095)	0.032	(0.070)	0.071	(0.097)	0.059	(0.077)	−0.070	(0.109)
Years from BA to Ph.D.^{2}	−0.008	(0.002) ***	−0.099	(0.230)	−0.003	(0.003)	−0.781	(0.412) †	−0.002	(0.003)	−0.001	(0.004)	−0.001	(0.003)	0.005	(0.004)
Research University II	−0.192	(0.091) *	0.133	(0.174)	0.085	(0.119)	0.105	(0.225)	−0.277	(0.136) *	0.303	(0.244)	0.234	(0.132) †	−0.023	(0.240)
Doctorate Granting I & II	−0.461	(0.100) ***	0.243	(0.175)	−0.006	(0.126)	−0.005	(0.221)	−0.030	(0.135)	0.203	(0.228)	0.081	(0.140)	−0.015	(0.258)
Other	0.159	(0.150)	−0.099	(0.230)	0.073	(0.234)	−0.781	(0.412) †	0.680	(0.179) ***	−0.732	(0.308) *	0.591	(0.207) **	−0.859	(0.374) *
Family Characteristics																
Family structure at time of survey (excluded = No children)																
Children aged < 2 years	−0.184	(0.076) *	0.212	(0.149)	0.165	(0.099) †	0.127	(0.206)	0.182	(0.107) †	−0.350	(0.218)	−0.226	(0.122) †	0.326	(0.244)
Children aged 2–5 years	−0.087	(0.078)	0.195	(0.164)	0.060	(0.104)	0.305	(0.211)	−0.037	(0.111)	0.452	(0.217) *	0.150	(0.113)	−0.078	(0.249)
Children aged 6–17 years	−0.234	(0.099) *	0.277	(0.195)	0.186	(0.115)	−0.042	(0.232)	−0.107	(0.127)	0.233	(0.235)	0.071	(0.126)	−0.057	(0.264)
Marital status/Spouse's work status (reference = Unmarried)																
Spouse works full time	−0.354	(0.073) ***	0.095	(0.120)	−0.118	(0.108)	−0.003	(0.176)	−0.356	(0.109) ***	0.353	(0.174) *	−0.081	(0.122)	−0.016	(0.189)
Spouse works part time	−0.331	(0.114) **	0.000	(0.271)	0.302	(0.146) *	0.161	(0.327)	−0.073	(0.157)	−0.209	(0.398)	0.275	(0.161) †	−0.635	(0.418)
Spouse does not work	−0.519	(0.085) ***	0.388	(0.196) *	0.016	(0.120)	0.079	(0.264)	−0.436	(0.125) ***	0.335	(0.275)	−0.064	(0.145)	0.270	(0.311)
Model goodness-of-fit statistics																
Sample (n)									17,153							
Wald χ^2 (df)									3607.93 (160)							
Pseudo R^2									0.119							

† $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$; Source: Author's calculations using data from the *Survey of Doctorate Recipients* [22] and the *O*NET Occupational Information Network Database* [23], 1995–2013.

Table A4. Estimated coefficients from logit models of employment at a R1 or R2 university among those attaining a postdoctoral position or a tenure-track faculty appointment.

	Main Effect		* Female	
	b	**se(*b*)**	***b***	**se(*b*)**
Constant	–6.693	(1.226) ***		
Female	–1.376	(0.462) **		
Year	0.108	(0.024) ***	0.030	(0.039)
Year^2	–0.003	(0.001) *	–0.002	(0.002)
Demographic characteristics				
Age	0.443	(0.071) ***		
Age^2	–0.005	(0.001) ***		
U.S. citizen	–0.324	(0.068) ***		
Race (reference = White, non-Hispanic)				
Black, non-Hispanic	–0.297	(0.130) *		
Asian or Pacific Islander, non-Hispanic	–0.151	(0.071) *		
Hispanic	–0.028	(0.105)		
Other, non-Hispanic	–0.356	(0.241)		
Degree field (reference = Mathematical & computer sciences)				
Biological sciences	0.303	(0.103) **	0.072	(0.197)
Physical, chemical and earth sciences	0.016	(0.106)	–0.031	(0.212)
Engineering	0.477	(0.106) ***	–0.167	(0.228)
Educational background				
Years from BA to Ph.D.	–0.353	(0.051) ***	0.188	(0.078) *
Years from BA to Ph.D.^{2}	0.010	(0.002) ***	–0.008	(0.003) *
Carnegie class of doctorate-granting institution (reference = Research University I)				
Research University II	–0.352	(0.097) ***	0.060	(0.180)
Doctorate Granting I & II	–1.146	(0.132) ***	0.247	(0.217)
Other	–0.851	(0.149) ***	–0.089	(0.231)
Family Characteristics				
Family structure at time of survey (reference = No children)				
Children aged < 2 years	–0.076	(0.083)	0.053	(0.151)
Children aged 2–5 years	–0.021	(0.081)	–0.048	(0.156)
Children aged 6–17 years	–0.021	(0.088)	0.284	(0.177)
Marital status/Spouse's work status (reference = Unmarried)				
Spouse works full time	–0.068	(0.080)	0.128	(0.128)
Spouse works part time	0.025	(0.113)	0.129	(0.254)
Spouse does not work	–0.026	(0.097)	–0.149	(0.200)
Employment Sector (reference = Postdoctoral position)				
Faculty position, tenure-track	–0.555	(0.077) ***	–0.078	(0.131)
Model goodness-of-fit statistics				
Sample (n)	9850			
Wald χ^2 (df)	548.25 (42)			
Pseudo R^2	0.063			

*$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$. *Source*: Author's calculations using data from the *Survey of Doctorate Recipients* [22] and the *O*NET Occupational Information Network Database* [23], 1995–2013.

Table A5. Estimated coefficients from regression models of job characteristics and salary among full-time employed STEM doctorates.

	Doctorate Required in Occupation		Work Is Related to Degree Field		Research Is Primary Work Activity		Percent Female in Occupation		Salary (among All Full-Time Workers)	
	b	se(*b*)	*b*	se(*b*)	*b*	se(*b*)	*b*	se(*b*)	*b*	se(*b*)
Constant	–2.514	(1.222) *	–2.629	(1.058) *	0.235	(1.019)	1.844	(0.514) ***	10.097	(0.183) ***
Female	–0.470	(0.330)	0.415	(0.320)	–0.382	(0.322)	0.557	(0.138) ***	–0.032	(0.054)
Year	0.012	(0.024)	0.018	(0.021)	–0.010	(0.020)	0.097	(0.009) ***	–0.016	(0.004) ***
* Female	–0.054	(0.045)	–0.002	(0.042)	–0.073	(0.037) †	–0.028	(0.014) †	0.007	(0.007)
Year^2	–0.001	(0.001)	–0.001	(0.001)	0.000	(0.001)	–0.003	(0.000) ***	0.001	(0.000) ***
* Female	0.002	(0.002)	0.000	(0.002)	0.004	(0.002) *	0.001	(0.001)	0.000	(0.000)
Demographic characteristics										
Age	–0.035	(0.072)	–0.028	(0.061)	–0.011	(0.059)	0.041	(0.027)	0.039	(0.011) ***
Age^2	0.000	(0.001)	0.001	(0.001)	0.000	(0.001)	–0.001	(0.000)	0.000	(0.000) *
U.S. citizen	0.252	(0.073) ***	0.110	(0.067)	–0.012	(0.062)	0.054	(0.021) **	0.060	(0.012) ***
Race (reference = White, non-Hispanic)										
Black, non-Hispanic	0.330	(0.136) *	–0.049	(0.138)	–0.086	(0.126)	0.054	(0.050)	–0.043	(0.021) *
Asian or Pacific Islander, non-Hispanic	0.235	(0.076) **	0.046	(0.069)	0.125	(0.065) †	0.035	(0.023)	–0.018	(0.013)
Hispanic	–0.085	(0.127)	0.221	(0.103) *	0.063	(0.106)	0.094	(0.025) ***	–0.025	(0.016)
Other, non-Hispanic	0.535	(0.274) †	0.202	(0.235)	–0.041	(0.213)	0.032	(0.049)	0.026	(0.025)
Degree field (reference = Mathematical & computer sciences)										
Biological sciences	1.292	(0.101) ***	–0.494	(0.126) ***	–0.941	(0.120) ***	0.399	(0.042) ***	–0.182	(0.019) ***
Physical, chemical and earth sciences	0.778	(0.101) ***	–0.918	(0.109) ***	0.292	(0.097) **	–0.011	(0.043)	–0.107	(0.020) ***
Engineering	–1.614	(0.088) ***	–0.176	(0.088) *	0.241	(0.080) **	–0.442	(0.037) ***	0.003	(0.021)
Educational background										
Years from BA to Ph.D.	–0.113	(0.050) *	0.032	(0.044)	0.006	(0.043)	–0.054	(0.016) ***	–0.031	(0.007) ***
Years from BA to Ph.D.^{2}	0.004	(0.002) *	–0.001	(0.002)	0.000	(0.002)	0.002	(0.001) **	0.001	(0.000) **
Carnegie classification of doctorate-granting institution (reference = Research University I)										
Research University II	0.187	(0.085) *	0.000	(0.079)	0.124	(0.069) †	–0.013	(0.030)	–0.075	(0.016) ***
Doctorate Granting I & II	–0.076	(0.096)	–0.029	(0.084)	0.069	(0.077)	0.024	(0.029)	–0.080	(0.020) ***
Other	0.360	(0.139) **	0.093	(0.121)	0.021	(0.135)	–0.068	(0.060)	–0.017	(0.016)
Family Characteristics										
Family structure at time of survey (reference = No children)										
Children aged <2 years	0.056	(0.085)	–0.135	(0.071) †	0.009	(0.073)	0.039	(0.026)	–0.015	(0.015)
* Female	–0.107	(0.192)	0.259	(0.163)	0.081	(0.162)	–0.082	(0.060)	0.027	(0.026)
Children aged 2–5 years	0.008	(0.087)	0.093	(0.071)	0.038	(0.071)	–0.011	(0.028)	0.001	(0.014)
* Female	–0.036	(0.203)	–0.265	(0.181)	0.136	(0.166)	0.019	(0.043)	0.023	(0.025)

Table A5. *Cont.*

	Doctorate Required in Occupation		Work Is Related to Degree Field		Research Is Primary Work Activity		Percent Female in Occupation		Salary (among All Full-Time Workers)	
	b	**se(*b*)**	***b***	**se(*b*)**	***b***	**se(*b*)**	***b***	**se(*b*)**	***b***	**se(*b*)**
Children aged 6–17 years	–0.084	(0.098)	0.030	(0.083)	–0.130	(0.085)	–0.046	(0.039)	0.015	(0.012)
* Female	–0.026	(0.199)	0.011	(0.139)	–0.308	(0.166) †	0.044	(0.058)	–0.013	(0.028)
Marital status/Spouse's work status (reference = Unmarried)										
Spouse works full time	0.130	(0.090)	0.031	(0.079)	0.116	(0.078)	–0.008	(0.030)	0.025	(0.012) *
* Female	–0.194	(0.151)	0.093	(0.142)	–0.117	(0.137)	0.004	(0.041)	–0.023	(0.021)
Spouse works part time	–0.025	(0.125)	0.287	(0.101) **	0.126	(0.107)	0.019	(0.031)	0.057	(0.015) ***
* Female	0.351	(0.271)	–0.004	(0.215)	0.044	(0.234)	0.014	(0.068)	–0.110	(0.041) **
Spouse does not work	0.102	(0.097)	0.160	(0.083) †	0.160	(0.084) †	–0.023	(0.033)	0.065	(0.014) ***
* Female	–0.261	(0.238)	0.038	(0.181)	–0.339	(0.181) †	–0.027	(0.079)	–0.078	(0.030) **
Employment characteristics										
Hours worked	0.027	(0.003) ***	0.001	(0.003)	0.000	(0.000) ***	0.001	(0.001)	0.002	(0.001) **
Employment sector (reference = Postdoctoral position)										
Faculty, tenure track									0.342	(0.016) ***
* Female									–0.045	(0.026) †
Faculty, not tenure track									0.185	(0.022) ***
* Female									–0.021	(0.033)
Other academic or government	–0.700	(0.132) ***	0.045	(0.101)	0.237	(0.103) *	–0.128	(0.042) **	0.431	(0.018) ***
* Female	0.174	(0.229)	0.122	(0.174)	0.033	(0.177)	0.064	(0.051)	–0.076	(0.032) *
Business or industry	–0.422	(0.100) ***	0.128	(0.080)	0.523	(0.085) ***	–0.142	(0.028) ***	0.620	(0.015) ***
* Female	0.573	(0.167) ***	0.013	(0.152)	–0.033	(0.149)	–0.008	(0.037)	–0.045	(0.026) †
Doctorate required in occupation			0.009	(0.002) ***	0.017	(0.002) ***	0.003	(0.000) ***	0.039	(0.024) †
* Female			–0.001	(0.003)	0.001	(0.003)	–0.001	(0.001) *	–0.023	(0.040)
Field-occupation relatedness	0.009	(0.002) ***	0.000	(0.000) ***	0.048	(0.002) ***	0.001	(0.001)	0.010	(0.029)
* Female	0.003	(0.003)	0.000	(0.000) ***	0.006	(0.003) *	0.000	(0.001)	–0.002	(0.042)
Research is primary work activity	0.034	(0.002) ***	0.070	(0.001) ***			0.001	(0.001)	–0.013	(0.035)
* Female	0.007	(0.003) †	–0.003	(0.003)			–0.003	(0.001) **	0.048	(0.050)
Model goodness-of-fit statistics										
Sample (n)	9199		9199		9199		9199		17,144	
R^2	0.366		0.516		0.388		0.281		0.249	

† $p \leq 0.10$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$. Source: Author's calculations using data from the *Survey of Doctorate Recipients* [22] and the *O*NET Occupational Information Network Database* [23], 1995–2013.

Appendix B. Measuring the Relationship between STEM Doctoral Degrees and Occupations

Attainment of a doctoral degree in a STEM field represents a significant investment in specialized education, and a strong commitment to a career in a STEM field. Utilizing that investment entails gaining employment in job that requires the use of the specialized knowledge and skills developed through educational experiences [28]. The underutilization of the education, skills, and expertise of women who invested in STEM fields is well-documented (for example, see [3,29–31]).

Attaining employment as a tenure-track faculty member at a research-intensive university is the ideal labor market application of a STEM doctorate because such employment fully utilizes the educational capital the STEM doctorate represents. Other types of employment vary in the degree to which they utilize doctoral-level training in a STEM field: some jobs will rival the research university faculty position in their demand for specialized skills and training, some will demand only some of the skills and specialized knowledge gained in the pursuit of a STEM doctorate, while the performance of others will demand none of those skills.

Prior research on gender differences in the utilization of science and engineering educational investments, i.e., research on gender differences in the "science pipeline," has exclusively relied on a researcher-imposed operationalization of educational utilization [3]. In this approach, researchers classify a set of occupations as those that comprise the STEM labor market, and employment in one of these occupations is defined as the utilization of STEM education. The researcher-imposed classification may be based on any combination of independent judgment, the conventions of prior research, or classification schemes used by benchmarking entities [6,7].

Although the researcher-defined approach is reasonable, it has significant limitations which may produce biased estimates of the degree to which STEM doctorates utilize their education in the labor market, i.e., the degree to which they stay in the "pipeline." First, it relies on the judgment of the researcher, rather than on the assessment of the individuals whose education-work transition is being observed or on an empirical method of measuring the substantive consistency of education-occupation pairing. As such, it is likely to be strongly influenced by the something as relatively capricious as the labeling of the categories in the classification scheme. The researcher-defined approach also ignores the fact that occupational categories combine jobs that may differ in the degree to which they are related to a STEM degree. This variability cannot be reflected in the dichotomous nature of the researcher-defined operationalization, nor can the education-occupations "linkages" identified by a binary indicator variable capture the relative strength of education-occupation connections [28].

To obtain unbiased estimates of gender differences in the attainment of employment that utilizes STEM education, I operationalize education-occupation relatedness by measuring the degree to which an occupation requires doctorate-level education, demands research skills, and is substantively related to their degree field. The level of education required for employment in a given job is a basic measure of whether one's education will be utilized on the job. For doctorates, the extent to which a doctoral degree is required by the jobs in an occupational category is a first-order measure of whether an occupation is commensurate with their educational investment. Second, since doctoral-level education in STEM fields is devoted to the training of research skills, I use the extent to which research is a primary work activity to capture another dimension of education-occupation relatedness. Third, I use the degree to which an occupation is related to various STEM fields as a measure of the substantive education-occupation relatedness. Using these measures of educational utilization to track employment outcomes may provide a new understanding of where in the labor market the science pipeline leads and to what extent those pathways differ by gender.

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A Tale of Two Majors: Explaining the Gender Gap in STEM Employment among Computer Science and Engineering Degree Holders

Sharon Sassler [1,*], Katherine Michelmore [2] and Kristin Smith [3]

1. Department of Policy Analysis & Management, Cornell University, The College of Human Ecology, 297 Martha Van Rensselaer Hall, Ithaca, NY 14853, USA
2. Department of Public Administration and International Affairs, The Maxwell School, Syracuse University, 426 Eggers Hall, Syracuse, NY 13244-1090, USA; kmmichel@syr.edu
3. Department of Sociology and Carsey School of Public Policy, University of New Hampshire, Huddleston Hall, 73 Main Street, Durham, NH 03824, USA; kristin.smith@unh.edu

* Correspondence: ss589@cornell.edu; Tel.: +1-607-254-6551

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Abstract: We examine factors contributing to the gender gap in employment in science, technology, engineering, and math (STEM) among men and women with bachelor's degrees in computer science and engineering, the two largest and most male-dominated STEM fields. Data come from the National Science Foundation's (NSF) Scientists and Engineers Statistical Data System (SESTAT) from 1995 to 2008. Different factors are associated with persistence in STEM jobs among computer science and engineering degree holders. Conditional on receiving a degree in computer science, women are 14 percentage points less likely to work in STEM than their male counterparts. Controlling for demographic and family characteristics did little to change this gender gap. Women with degrees in engineering are approximately 8 percentage points less likely to work in STEM than men, although about half of this gap is explained by observed differences between men and women. We document a widening gender gap in STEM employment in computer science, but this gender gap narrows across college cohorts among those with degrees in engineering. Among recent computer science graduates, the gender gap in STEM employment for white, Hispanic, and black women relative to white men is even larger than for older graduates. Gender and race gaps in STEM employment for recent cohorts of engineering graduates are generally small, though younger Asian women and men no longer have an employment advantage relative to white men. Our results suggest that a one-size-fits-all approach to increasing women's representation in the most male-dominated STEM fields may not work.

Keywords: gender; scientists and engineers; STEM employment; gender inequality

1. Introduction

During the later third of the 20th century, the science and technology labor force diversified in important ways. Women's graduation rates in science, technology, engineering, and mathematics (STEM) increased between two and ten times since the 1970s (Committee on Maximizing the Potential of Women in Academic Science and Engineering (U.S.) and Committee on Science, Engineering, and Public Policy (U.S.) (2007)). However, even among women who held degrees in STEM fields, employment in STEM jobs continues to lag that of their male counterparts. Women who graduate with degrees in STEM majors are less likely than their male counterparts to enter STEM occupations, or remain in them (Glass et al. 2013; Ma and Savas 2014; Mann and DiPrete 2013; Sassler et al. 2017). Historically, women were often discouraged from pursuing employment outside the home, particularly in jobs—such as those in STEM—typically thought of as "masculine" (Robinson and McIlwee 1991).

Gender differences in human capital accumulation, occupational concentration, work history, and discrimination also differentiated the likelihood that women worked in STEM jobs. As women have increased their participation in the workforce and obtained college and advanced degrees, some of these explanations have faded in importance; others, such as differences in the working patterns of men and women, continue to have an impact on earnings differentials (Blau and Kahn 2006; Mandel and Semyonov 2014) and occupational attainment (Weeden et al. 2016).

Tremendous resources have been devoted to increasing women's representation in STEM employment (Committee on Maximizing the Potential of Women in Academic Science and Engineering (U.S.) and Committee on Science, Engineering, and Public Policy (U.S.) (2007)). Such efforts are based on the belief that increasing women's representation in STEM occupations will encourage more women to pursue such fields of study, and remain in the STEM work force (Fouad et al. 2011; Hill et al. 2010). The increased representation of women could also have the long-term effect of diversifying leadership in STEM jobs, and expanding women's access to mentoring and leadership positions (Preston 2004; Stephan and Levin 2005). In fact, among the most widely cited impediments to greater diversification of the STEM labor force are perceptions of being isolated, reported by many women who are employed in fields, such as engineering and computer science, where their representation is the smallest (Fouad et al. 2011; Gunter and Stambach 2005; Kanter 1977; Michelmore and Sassler 2016). Others attribute the dearth of women in some STEM fields, and disparities in wages, to discrimination, though the evidence suggests that discrimination has diminished as a contributor to the gender earnings gap, if not to the employment gap in particular fields (Mandel and Semyonov 2014; Michelmore and Sassler 2016). Despite a good deal of public discourse on the challenging climate facing women in computer science and engineering, additional empirical research is needed to better understand what factors contribute to the gender employment gap in these fields.

In the two largest and most male-dominated STEM fields, computer science and engineering, there have been opposing demographic shifts in the composition of degree holders over time. In computer science, the representation of women as a share of degree holders has fallen significantly even as the composition of female graduates has diversified. Women made up over one-third of graduates in the mid-1980s; in recent years, that share has fallen. By 2013, the share of bachelor's degrees in computer science that were being awarded to women was only half of what it had been in the 1980s (Corbett and Hill 2015). In engineering, in contrast, the opposite trend is seen. Although still heavily male-dominated, women have increased their representation in engineering ten-fold since 1970, going from 2% of majors in 1970, to 22% of majors in 2004 (Michelmore and Sassler 2016). However, degree receipt alone is not an adequate proxy of success in increasing shares of women in employment, as numerous studies make clear (e.g., Corbett and Hill 2015; Glass et al. 2013; Sassler et al. 2017). How these demographic shifts in the composition of STEM graduates have affected the gender gap in employment in STEM is an empirical question.

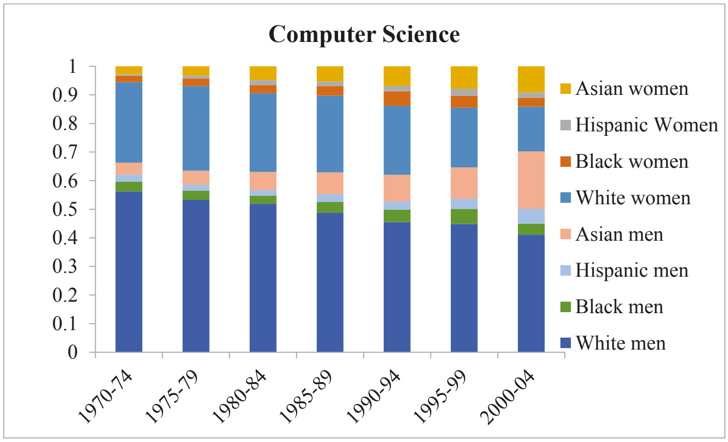
In this paper, we answer this question by examining the factors that contribute to the gender gap in STEM employment among those who received a bachelor's degree in computer science or engineering over the last four decades. We focus our analysis on these two fields because they represent the largest share of STEM jobs and are the two STEM fields in which women make up the smallest share of college majors. Using data from the National Science Foundation's (NSF) Scientists and Engineers Statistical Data System (SESTAT) from 1995 to 2008, we first illustrate the large demographic shifts that occurred in these two fields between 1970 and 2004—with computer science experiencing a large decline in the number of female degree holders, and engineering experiencing an increase in women degree holders. We then document the overall gender gap in persistence in STEM occupations among these individuals, testing to what extent gaps can be explained by differences in observable characteristics between men and women. Finally, we analyze how the large demographic shifts in the composition of computer science and engineering degree holders has influenced the gender gap in STEM employment over time through a cohort analysis.

Results from our analysis shed light on the factors associated with persistence in STEM occupations, and how the gender gap in persistence in STEM has changed over the last several decades. Our results reveal two distinct portraits of women's experiences in the two largest and most male-dominated STEM fields. Among recent cohorts, women's representation of computer science graduates has declined. Women who *do* obtain degrees in computer science are increasingly less likely to work in STEM occupations relative to their male peers. In contrast, as women have increased their representation in engineering over the last several decades, gender gaps in working in STEM appear to have stabilized. As a result, the share of women graduates who work in engineering is at near parity with men in recent cohorts. Our results suggest that the barriers to employment for women in computer science likely differ from those deterring even larger increases in women's representation in engineering. Such findings highlight the very real need to address roadblocks—such as a challenging and often unwelcoming work climate, gender bias and discriminatory treatment, and the negation of relationship and family responsibilities—that deter more women from majoring in and remaining in computer science jobs.

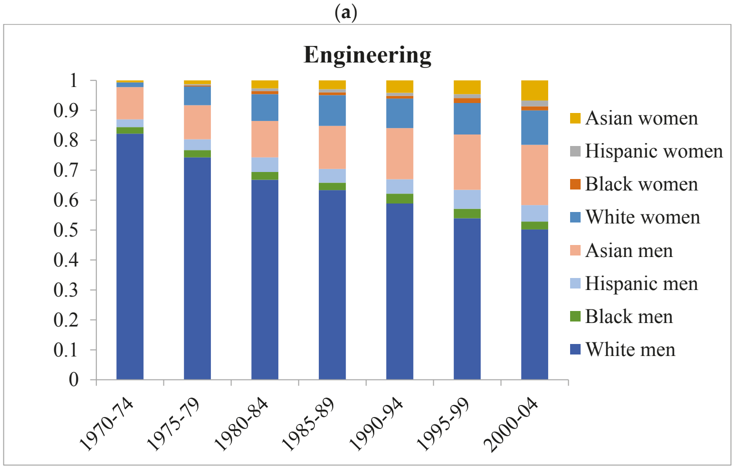
2. Understanding the Gender Gap in Women's Employment in STEM Occupations

Among one of the more frequent explanations for why women were underrepresented in STEM professions in the closing decades of the 20th century was one that drew on gender essentialism, namely that women were less interested in STEM topics, and therefore unlikely to pursue the training necessary to work in the STEM labor force. Historically, women who pursued bachelor's degrees have been far less likely than men to major in STEM, instead obtaining degrees in humanities or liberal arts subjects (Shauman 2006; Xie and Killewald 2012). A gender essentialist argument overlooks the social nature of gender, and the many barriers that prevented women's entrance into STEM studies and occupations (Charles and Grusky 2004). In fact, the gender composition of STEM fields varies a great deal across countries (Charles and Bradley 2006; Charles and Bradley 2009), suggesting cross-cultural variation in occupations that are considered "masculine" or "feminine." In recent years, there has been a substantial increase in the proportion of female STEM graduates in the United States. In the early years of the 21st century, women accounted for the majority of all college graduates with degrees in the life sciences, and approximately 40% of those graduating with degrees in the physical sciences (Michelmore and Sassler 2016).

In computer science and engineering, women continue to make up a distinct minority of graduates: women account for approximately one-third of graduates in computer science, and one-fifth of graduates in engineering. Women's representation in computer science, however, has actually declined in recent years. We illustrate this in Figure 1, where we present the gender and race composition of computer science and engineering degree holders since 1970. Computer science has become more male-dominated in recent years, due in large part to an influx of Asian men into the computer science major. White women's representation in computer science, on the other hand, has declined substantially: from 28% during 1970–1974, to just 15% during 2000–2004. The decline in women's representation in computer science would be even more dramatic, were it not for the increase in representation among minority women, primarily black and Asian women. Engineering, on the other hand, has seen a very different pattern over the last several decades. Among graduates during 1970–1974, white men made up more than 80% of degree holders, and women as a whole accounted for just 2% of graduates. Over time, women have increased their representation, accounting for approximately 22% of graduates during 2000–2004. While the representation of white women among engineering graduates has grown, there have also been increases of other women, particularly Asian women. In addition to contributing to the gender wage gap, women's underrepresentation in engineering and computer science majors accounts for a sizable proportion of the gender employment gap in STEM occupations, as these two fields account for about three-quarters of jobs in STEM (Corbett and Hill 2015; Michelmore and Sassler 2016; Xie and Killewald 2012).



(**a**)



(**b**)

Figure 1. Race and gender distribution of computer science and engineering majors by college cohort: (**a**) Computer Science Majors; (**b**) Engineering Majors. Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004.

In recent years, the evidence suggests that among those who complete degrees in STEM fields, the gender gap in transitions into STEM employment is minimal initially, and women appear as likely to transition into STEM jobs as their male counterparts, though computer science remains an exception (Smith-Doerr 2004). However, increasing the representation of women pursuing and obtaining STEM degrees is not enough to narrow the gender gap in STEM employment, as the pipeline continues to leak after degree receipt. The evidence suggests that retention of women in STEM professions is a challenge. Women in STEM occupations are significantly more likely to exit STEM employment than are women in other challenging fields, such as law or business (Glass et al. 2013), or men in STEM occupations (Fouad et al. 2011; Hunt 2016; Preston 2004).

The explanation most frequently proffered for gender discrepancies in professional job retention tend to revolve around challenges with balancing work and family life. Some scholars argue that persistent gender differences in labor market retention can be attributed to the discrepancy between women's and men's willingness to prioritize work demands over family obligations (Ceci and Williams 2011; Ferriman et al. 2009; Hakim 2000; Hakim 2002), though attributing differential behavior to preferences is strongly critiqued by feminist scholars as essentialist (Halrynjo and Lyng 2009; Stähli et al. 2009). The relational and family care obligations of marriage, for example, appear to be greater for women than men; perhaps as a result, women with STEM degrees are less likely than their male counterparts to be married (Mason et al. 2013).

Nonetheless, recent research has challenged the long-accepted belief that family constraints, such as the presence of children, contribute to differential retention of women in STEM occupations (Glass et al. 2013; Hunt 2016). Hunt (2016) showed that the gendered persistence gap in engineering was almost entirely due to dissatisfaction with pay and promotion, rather than resulting from family constraints. Glass and colleagues (2013) found that women exited STEM within a few years of college completion, often prior to marriage and having children. Nonetheless, among those who persisted in STEM jobs post marriage and childbearing, having a second or higher order child exacerbated women's odds of exiting from STEM jobs to a considerably greater extent than it did for other professional jobs (Glass et al. 2013). Research on how marriage and children influence men's attrition from the STEM labor force is non-existent, although descriptive evidence suggests that men are increasingly influenced by perceptions that STEM fields are not amenable to family life (Mason et al. 2013). There is also some evidence that the association between children and earnings—a central factor shaping retention (Hunt 2016)—has changed among more recent cohorts of women, at least for some segments; among professional women, the association between motherhood and wages has become positive (Buchmann and McDaniel 2016; Michelmore and Sassler 2016; Pal and Waldfogel 2016). This likely reflects, to some extent, selection issues into both motherhood and working among recent cohorts of professional women.

While family factors may matter less for attrition from the STEM labor force among more recent cohorts, particularly among women, the stock of STEM workers is shaped by the historical experiences of earlier graduates. In other words, gender gaps in STEM employment could be due to the labor force exits of earlier cohorts of women employed in STEM. Previous cohorts of women were more likely than men to have taken time out of the labor force, or to have reduced their hours of employment, to have and raise children (Bertrand et al. 2010; Budig and England 2001; Byker 2016; Goldin 2014). Older cohorts of women may also have exited the STEM work force due to frustration over lack of promotion or experiences with discrimination. The evidence suggests that the passage of equal employment legislation has reduced the impact of discrimination as a contributor to the gender earnings gap in the overall labor market between 1970 and 2010 (Mandel and Semyonov 2014), and perhaps in employment as well. Nonetheless, recent studies employing experimental designs have revealed how implicit bias and gendered stereotypes operate to privilege men over women in the hiring process, while also shaping pay and mentoring (Moss-Racusin et al. 2012). Still, female employment throughout the life course has become increasingly normative, leading us to expect the gender gap in employment to narrow among more recent graduates.

In this paper, we expand on prior work analyzing the gender gap in STEM employment. Our analysis uses a broad range of cohorts of college graduates, and we focus on the two STEM professions that account for the largest share of STEM workers. Our sample includes all men and women holding bachelor's degrees in either computer science or engineering, unlike some prior work that focused on PhD holders (e.g., Mason et al. 2013; Shauman 2017). We begin by illustrating the gender gap in retention in STEM occupations, separately for computer science and engineering degree holders. We next use regression analysis to illustrate how the gender gap in working in STEM changes with the addition of controls for race/ethnicity, immigrant status, college cohort, advanced degree holding, and family characteristics. Finally, given the large demographic shifts in these two fields over the last several decades, we examine how the gender gap in persistence in STEM has changed across college cohorts from 1970 to 2004.

3. Data and Method

Data come from the National Science Foundation's (NSF) Scientists and Engineers Statistical Data System (SESTAT). We incorporate data from six waves of the SESTAT data collection: 1995, 1997, 1999, 2003, 2006, and 2008. SESTAT is comprised of three ongoing surveys designed to create a nationally representative sample of science and engineering college degree holders. We utilize the integrated data, which include data from the National Survey of College Graduates Science and Engineering Panel, the National Survey of Recent College Graduates, and the Survey of Doctoral Recipients. SESTAT participants have all received at least a bachelor's degree and have at least one degree in science or engineering, or are individuals holding any college degree that work in a science or engineering occupation. The restricted SESTAT data include detailed information regarding labor force participation, occupation categories, educational attainment, and demographic characteristics.

We treat the data as repeated cross-sections, although some respondents appear in more than one wave of data. To reduce concerns of non-independent sampling, we restrict our analysis to one observation per person, choosing a survey wave at random for individuals represented in multiple waves. We further limit our analysis to men and women who received a bachelor's degree in either computer science or engineering between 1970 and 2004. Since data are collected between 1995 and 2008, this cohort restriction limits the sample to working-aged individuals (aged 22 to 60). We further limit our sample to individuals who are working, excluding individuals who are unemployed, in school, or out of the labor force. This restriction reflects our interest in understanding the factors that determine men and women's decisions to work in STEM occupations relative to other non-STEM occupations. Results from our analysis of the gender gap in STEM can therefore be interpreted as the difference in men and women's propensity to work in STEM compared to other employment outside of STEM occupations. Labor force participation is quite high among this sample: these restrictions omit 7% of men and 14% of women with degrees in computer science or engineering.[1] Our final sample consists of 55,895 men and women working (in any occupation) with bachelor's degrees in computer science or engineering.

4. Measurement

Dependent variable: Our dependent variable of interest is a binary indicator for whether the individual was working in a STEM occupation at the time of the interview. The SESTAT data contain detailed occupation codes for all employed individuals in the survey. Individuals working in one of the four main STEM fields were considered working in STEM (computer science, engineering, life sciences, or physical sciences), while individuals who were employed outside of the STEM fields were considered not working in STEM. While we analyze results separately for computer science and engineering majors, we do not restrict STEM majors to work in the occupation they majored in. That is, respondents who majored in computer science and work as life scientists are considered working in STEM, just as computer science majors working in computer science are also considered working in STEM. A list of STEM occupations can be found in Table A1, along with the share of STEM workers working in each of the occupations. Table A1 also lists the top occupation categories for individuals not working in STEM.

Approximately 90% of computer science majors who work in STEM are working in computer science or math-related occupations. Among engineering majors, 74% of those who are working in a STEM occupation are working in an engineering occupation. Another 16% of engineering majors are working in computer science. Among those not working in a traditional STEM field, the top occupations were science and engineering managers, science and engineering pre-college teachers,

1 Our main findings are consistent if we include individuals who are unemployed, in school, or out of the labor force and consider them "not working in STEM". Gender gaps are slightly larger, reflecting the fact that women are more likely to be out of the labor force relative to men (6% compared to 2% of men).

and science and engineering technicians.[2] These three fields accounted for roughly 40–45% of the occupations of non-STEM employed computer science and engineering degree holders in our sample.

As a sensitivity analysis, we also present results using a more restrictive definition of working in STEM (we refer to this as the "restricted" definition). In particular, we present results restricting the definition of working in STEM to include only the occupations that are in the respondent's major degree of study (i.e., computer science occupations for computer science majors and engineering occupations for engineering majors). These results reveal whether there is gender or racial variation in the propensity to work in STEM fields outside of the major field of study.

Independent variables: Our key independent variable of interest is the gender of the respondent. As a sensitivity check, we also estimate separate gender gaps in STEM employment for whites, blacks, Hispanics, and Asians by running regressions separately by race/ethnic group. Given the large foreign-born representation in the STEM work force (Sana 2010) we also include a dummy variable indicating whether respondents were born outside of the United States.

A number of controls are incorporated to account for the age and cohort structure of our sample. For starters, a linear control for the survey year of the SESTAT data is included in order to account for the variations in the propensity to work in STEM over time. We also utilized a linear control for age, to allow the propensity to work in STEM to vary by age. Last, we construct five-year college cohort indicators to account for the fact that the propensity to work in STEM may differ across college cohorts between 1970 and 2004; the 1970–1974 cohort serves as the comparison group.

We also include controls for whether the respondent obtained an advanced degree, differentiating among those with a master's degree in a STEM field, a PhD in a STEM field, and a non-STEM advanced degree. We expect that individuals with graduate degrees in STEM will be more likely to work in STEM compared to individuals with only a bachelor's degree or an advanced degree in a non-STEM field. Finally, we incorporate various controls for family characteristics. Separate indicators are constructed indicating whether the respondent is married or cohabiting, given that cohabitors espouse less traditional views regarding gender roles than do marrieds (Clarkberg et al. 1995). We also include a control for whether the respondent has any children, or any children under the age of six, the most time-intensive years. We also include interactions of all family characteristics with gender, to allow the association between family characteristics and propensity to work in STEM to differ for men and women. We expect family characteristics to be negatively associated with women's propensity to work in STEM, but to have no association with men's propensity to work in STEM.

Our analysis proceeds as follows. First, we describe differences in observed characteristics between men and women graduating with bachelor's degrees in computer science and engineering. We then turn to our multivariate analyses, using linear probability models to test whether differences between men and women in background characteristics, educational attainment, and family formation can account for the gender gap in persistence in STEM. A linear probability model has the advantage of allowing a straightforward interpretation of regression coefficients, particularly in evaluating how coefficients change across models. We test the sensitivity of our results using our restricted definition of what is considered a STEM occupation. Finally, we examine how the large demographic shifts in the composition of computer science and engineering degree recipients may have affected the gender gap in working in STEM by examining how the gender gap has evolved according to college cohort. This analysis will provide insight into whether the large demographic shifts in the race and gender composition of computer science and engineering graduates over the last several decades has correlated with shifts in the gender gap in persisting in STEM occupations. Since computer science and engineering have experienced very different demographic shifts over the last several decades, we present all results separately for these two fields.

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[2] Results including these occupations as STEM occupations revealed largely similar gender and race gaps in working in STEM.

5. Results

Descriptive statistics of those who majored in computer science or engineering are presented in Table 1, separately by major and gender. Underlined coefficients indicate significant differences in characteristics between men and women. The gender gap in working in STEM is much wider among computer science majors than among engineering majors. While 56% of male computer science majors in our sample were working in STEM at the time of the survey, the equivalent share of women was just 42% for female computer science majors, a gap of 14 percentage points. The gap is slightly narrower if we restrict our definition of "working in STEM" to include only working in computer science-related occupations (52% vs. 40%), reflecting the fact that male computer science majors are slightly more likely to be working in STEM occupations outside of the main computer science field.

Table 1. Descriptive Statistics of those who majored in Computer Science or Engineering, by Gender.

	Computer Science				Engineering			
	Men		Women		Men		Women	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Working in STEM	0.56	0.50	0.42	0.49	0.64	0.48	0.61	0.49
Working in STEM (restricted) *	0.52	0.50	0.40	0.49	0.49	0.50	0.45	0.50
Survey year	2002.8	4.39	2002.5	4.38	2002.5	4.48	2002.8	4.33
Age	37.80	9.40	37.60	9.23	39.20	9.50	35.02	8.11
Race/Ethnicity								
White	0.75	0.43	0.68	0.47	0.74	0.44	0.62	0.49
Black	0.06	0.24	0.10	0.30	0.03	0.17	0.07	0.26
Hispanic	0.05	0.21	0.05	0.22	0.06	0.23	0.07	0.25
Asian	0.15	0.35	0.17	0.37	0.17	0.38	0.24	0.43
Foreign born	0.20	0.40	0.23	0.42	0.25	0.44	0.30	0.46
College (BA) cohort								
1970–1974	0.09	0.29	0.09	0.28	0.12	0.32	0.02	0.12
1975–1979	0.08	0.28	0.09	0.28	0.12	0.32	0.06	0.24
1980–1984	0.13	0.34	0.13	0.34	0.18	0.38	0.17	0.38
1985–1989	0.19	0.39	0.20	0.40	0.18	0.39	0.20	0.40
1990–1994	0.19	0.39	0.20	0.40	0.18	0.38	0.21	0.41
1995–1999	0.16	0.37	0.17	0.37	0.14	0.35	0.20	0.40
2000–2004	0.15	0.36	0.12	0.33	0.08	0.27	0.14	0.35
Graduate Degrees								
Has a master's in STEM	0.17	0.38	0.16	0.36	0.25	0.43	0.27	0.44
Has a PhD in STEM	0.02	0.15	0.02	0.13	0.04	0.18	0.03	0.18
Has an advanced degree in non-STEM	0.11	0.32	0.14	0.35	0.14	0.34	0.12	0.33
Family Characteristics								
Married	0.67	0.47	0.65	0.48	0.75	0.44	0.63	0.48
Cohabiting	0.03	0.16	0.03	0.16	0.02	0.13	0.03	0.16
Has any kids	0.46	0.50	0.48	0.50	0.52	0.50	0.44	0.50
Has any kids <6	0.24	0.43	0.23	0.42	0.25	0.44	0.25	0.43
Number of Observations	10,229		5666		35,377		7889	

Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, who are employed at the time of the survey. Notes: Women with children are defined as those who have at least one child under the age of 18 living in the household. Marriage and cohabitation evaluated at the time of the survey. Underlined cells indicate significantly different from men at $p < 0.05$ level; * Restricted definition: working in a STEM occupation of same field as college degree.

While male and female computer science majors are of similar age (on average, 37 years old at the time of the survey), the racial composition of computer science majors is quite different for men and women. Three-quarters of male computer science majors are white, compared to just two-thirds of female computer science majors. Female computer science majors are more likely to be black or Asian, and are also more likely to be foreign-born, compared to male computer science majors. Aside from differences in the racial composition between male and female computer science majors, other observable characteristics are quite similar between the two groups. Female computer science majors are slightly less likely to have an advanced degree in STEM, but more likely to have an advanced degree in a non-STEM field compared to men (14% versus 11%, respectively). Somewhat surprisingly, male and female computer science majors have similar family characteristics: about two-thirds are married, about half have any children, and just under a quarter have any children under the age of six.

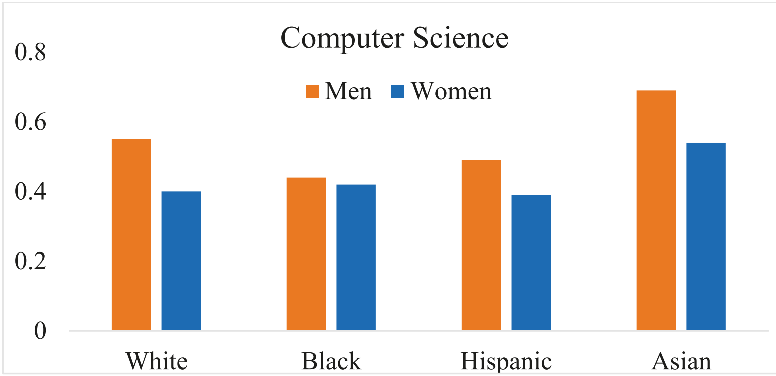
A different story emerges in engineering, where the gender gaps in working in STEM are much smaller, but the observable characteristics are quite different for men and women. The gender gap in working in STEM is just 3 percentage points when considering working in any STEM occupation in the four main STEM fields (64% of men compared to 61% of women), though this difference is statistically significant. Using our restricted definition of working in STEM, only 49% of men and 45% of women were working in STEM engineering occupations at the time of the interview. This lower retention reflects the migration of engineering majors into computer science-related fields (16%).

Despite the smaller gender gap in working in STEM, male and female engineering majors look quite different from each other. Male engineering majors are older than their female counterparts, indicating an influx of female engineers in more recent cohorts (39 years compared to 35 years on average, respectively). Similar to computer science, female engineering majors are more racially diverse than are male engineering majors, as three-quarters of male engineering majors are white, compared to just 62% of female engineering majors. Female engineering majors are more likely to be black than male engineering majors (7% versus 3%, respectively), and more likely to be Asian (24% versus 17%, respectively). Female engineering majors are also more likely than their male counterparts to be foreign-born (30% compared to 25%). Reflecting the age difference between male and female engineering majors, female engineering majors are more likely to have graduated from college (bachelor's degree) in 1995 or later. Less than 2% of the sample of female engineering majors graduated during 1970–1974, compared to 12% of male engineering majors. This reflects the large increase in female representation in engineering that has occurred over the last several decades.

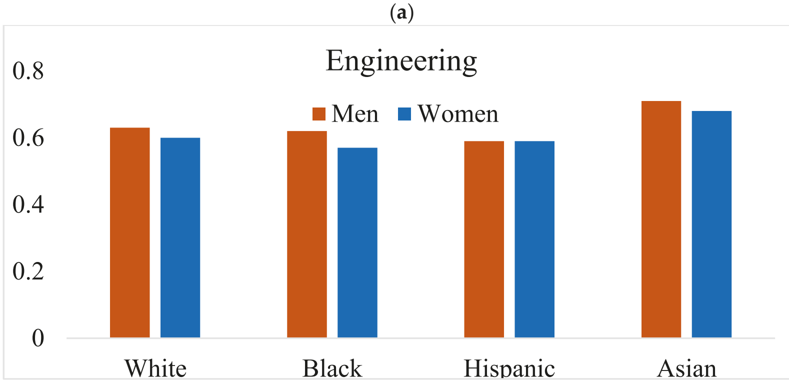
We also find significant differences in the family characteristics between male and female engineering graduates. Approximately three-quarters of male engineering degree holders were married, compared to just 63% of women. Women engineers were also somewhat more likely than their male counterparts to be cohabiting (3% versus 2%, though the difference is statistically significant), perhaps reflecting a desire to defer or avoid normative gender expectations that come with marriage. Male engineering majors were also more likely than their female counterparts in engineering to have any children (52% versus 44%). Still, women and men engineering graduates were equally likely to have young children (under age six) (25% of the sample). Some of these differences may be attributed to the younger average age of the female engineers, though others suggest the greater challenges to relationships for women committed to being professionals in demanding fields.

Among both computer science and engineering majors, women are less likely to be working in STEM occupations than men. These gender gaps are not uniform across racial groups, however. Figure 2 presents the share of men and women working in STEM for each of the four main race-ethnic groups in our sample, separately for computer science and engineering degree holders. In computer science, gender gaps in working in STEM are largest among whites and Asians; women are approximately 15 percentage points less likely to be working in STEM than their male counterparts in both of these groups. Gender gaps are much smaller among black and Hispanic computer science degree-holders. The gender gap for Hispanics is approximately 10 percentage points, while for blacks it is just 2 percentage points. For both men and women, black and Hispanic computer science degree holders are significantly less likely to be working in STEM compared to their white and Asian peers.

Among engineering degree holders, gender gaps in working in STEM are much narrower for all racial groups than in computer science. In engineering, the gender gap is actually widest between black men and women; black women are approximately 5 percentage points less likely to be working in STEM compared to black men. Among whites and Asians, women are approximately 3 percentage points less likely to be working in STEM relative to men. Among Hispanics, we find virtually no gender gap in working in STEM.



(**a**)



(**b**)

Figure 2. Share of men and women working in STEM among computer science and engineering degree holders, by race. (**a**) Computer Science Majors; (**b**) Engineering Majors. Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004.

6. Multivariate Results

We next turn to regression analyses to test whether background characteristics can explain some of the gender gap in the likelihood of working in STEM. Results for computer science graduates are presented in Table 2, while results for engineering graduates are presented in Table 3. We present models sequentially, first estimating the overall gender gap in the likelihood of working in STEM, then estimating gaps separately for each race/gender group, and subsequently adding controls for educational attainment and family characteristics to test whether differences in observable characteristics can explain part of the gender gap in STEM employment.

Table 2. Linear probability models predicting working in any STEM occupation: Computer science degree holders.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Survey Year		0.008 ***	0.007 ***	0.007 ***	0.001	0.0003	0.001	0.001
Age		−0.007 ***	−0.007 ***	−0.007 ***	0.0001	0.001	0.001	0.001
Gender and race								
Female	−0.136 ***	−0.136 ***						
White female			−0.148 ***	−0.149 ***	−0.147 ***	−0.136 ***	−0.134 ***	−0.123 ***
Black female			−0.146 ***	−0.149 ***	−0.16 ***	−0.145 ***	−0.139 ***	−0.128 ***
Hispanic female			−0.172 ***	−0.200 ***	−0.211 ***	−0.179 ***	−0.176 ***	−0.165 ***
Asian female			−0.038 **	−0.092 ***	−0.082 ***	−0.07 ***	−0.069 ***	−0.058 **
White male (ref)								
Black male			−0.114 ***	−0.122 ***	−0.133 ***	−0.113 ***	−0.111 ***	−0.111 ***
Hispanic male			−0.069 ***	−0.087 ***	−0.094 ***	−0.066 ***	−0.064 ***	−0.064 ***
Asian male			0.108 ***	0.056 ***	0.065 ***	0.043 ***	0.042 **	0.042 **
Foreign-born				0.069 ***	0.058 ***	0.009	0.008	0.008
BA cohort (ref: 1970–1974)								
1975–1979					0.106 ***	0.101 ***	0.109 ***	0.109 ***
1980–1984					0.196 ***	0.184 ***	0.192 ***	0.192 ***
1985–1989					0.226 ***	0.222 ***	0.226 ***	0.226 ***
1990–1994					0.224 ***	0.228 ***	0.228 ***	0.228 ***
1995–1999					0.291 ***	0.297 ***	0.297 ***	0.297 ***
2000–2004					0.283 ***	0.287 ***	0.289 ***	0.29 ***
Advanced degrees (ref: BA only)								
STEM master's						0.197 ***	0.195 ***	0.194 ***
STEM PhD						0.219 ***	0.217 ***	0.217 ***
Non-STEM advanced degree						−0.229 ***	−0.23 ***	−0.231 ***
Marriage and family								
Married							0.024 **	0.024 *
Cohabiting							−0.055 **	−0.033
Has kids							−0.047 ***	−0.042 ***
Has kids under 6							0.033 ***	0.037 ***
FemaleXMarried								0
FemaleXCohabiting								−0.065
FemaleXHas kids								−0.014
FemaleXHas kids under 6								−0.012
R-squared	0.016	0.036	0.044	0.046	0.057	0.111	0.1125	0.1125
N	15,895	15,895	15,895	15,895	15,895	15,895	15,895	15,895

Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, who are employed at the time of the survey. Notes: Results from linear probability model regressing an indicator for working in STEM on indicator for female and demographic characteristics. Women with children are defined as those who have at least one child under the age of 18 living in the household. Marriage and cohabitation evaluated at the time of the survey. Regressions weighted by person weights. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 3. Linear probability models predicting working in any STEM occupation: Engineering degree holders.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Survey Year		0.0003	−0.0001	0	−0.009 ***	−0.007 ***	−0.006 ***	−0.006 ***
Age		−0.011 ***	−0.011 ***	−0.011 ***	−0.003 ***	−0.002 ***	−0.002 ***	−0.002 ***
Gender and race								
Female	−0.028 ***	−0.074 ***						
White female			−0.083 ***	−0.082 ***	−0.080 ***	−0.079 ***	−0.080 ***	−0.030 **
Black female			−0.120 ***	−0.118 ***	−0.118 ***	−0.091 ***	−0.093 ***	−0.052 **
Hispanic female			−0.098 ***	−0.088 ***	−0.092 ***	−0.091 ***	−0.092 ***	−0.044 *
Asian female			−0.012	0.010	0.015	−0.013	−0.014	0.041 **
White male (ref)								
Black male			−0.026 *	−0.02	−0.028 **	−0.029 **	−0.029 **	−0.028 **
Hispanic male			−0.059 ***	−0.049 ***	−0.056 ***	−0.043 ***	−0.043 ***	−0.043 ***
Asian male			0.045 ***	0.068 ***	0.071 ***	0.045 ***	0.044 ***	0.043 **
Foreign-born				−0.029 ***	−0.028 ***	−0.062 ***	−0.061 ***	−0.060 ***
BA cohort (ref: 1970–1974)								
1975–1979					0.057 ***	0.051 ***	0.057 ***	0.056 ***
1980–1984					0.068 ***	0.069 ***	0.078 ***	0.077 ***
1985–1989					0.096 ***	0.089 ***	0.095 ***	0.094 ***
1990–1994					0.153 ***	0.148 ***	0.150 ***	0.149 ***
1995–1999					0.206 ***	0.190 ***	0.188 ***	0.186 ***
2000–2004					0.285 ***	0.253 ***	0.247 ***	0.244 ***
Advanced degrees (ref: BA only)								
STEM master's						0.154 ***	0.153 ***	0.154 ***
STEM PhD						0.111 ***	0.111 ***	0.110 ***
Non-STEM advanced degree						−0.278 ***	−0.277 ***	−0.278 ***
Marriage and family								
Married							−0.0004	0.006
Cohabiting							−0.059 ***	−0.049 **
Has kids							−0.030 ***	−0.026 ***
Has kids under 6							0.009	0.012 *
FemaleXMarried								−0.042 **
FemaleXCohabiting								−0.056
FemaleXHas kids								−0.040 **
FemaleXHas kids under 6								−0.017
R-squared	0.0004	0.045	0.0479	0.048	0.054	0.119	0.12	0.121
N	43,266	43,266	43,266	43,266	43,266	43,266	43,266	43,266

Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, who are employed at the time of the survey. Notes: Results from linear probability model regressing an indicator for working in STEM on indicator for female and demographic characteristics. Women with children are defined as those who have at least one child under the age of 18 living in the household. Marriage and cohabitation evaluated at the time of the survey. Regressions weighted by person weights. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

7. Computer Science Majors

With no other controls in the model, Model 1 shows that women who majored in computer science are 14 percentage points less likely to work in STEM compared to men who majored in computer science. In Model 2, we add controls for age and survey year. These controls do not mediate the relationship between gender and working in any STEM occupation.

Adding race to the model (Model 3) shows some heterogeneity in the gender/race gap among computer science majors in working in STEM. White, black, and Hispanic women are much less likely to work in STEM compared to white men (between 15 and 17 percentage points), while Asian women are only 4 percentage points less likely to work in STEM. Minority men are also less likely to work in STEM: black men are approximately 11 percentage points less likely to work in STEM and Hispanic men are 7 percentage points less likely to work in STEM compared to white men. Asian men, on the other hand, are significantly more likely to work in STEM than their white counterparts (11 percentage points). Including a control for whether the respondent is foreign-born (Model 4) explains some of the race gaps in working in STEM. Foreign-born computer science majors are 7 percentage points more likely to work in STEM compared to native-born respondents. This foreign-born advantage is explained by differences in the likelihood of obtaining higher degrees in STEM between native-born and foreign-born respondents, as the effect of being foreign-born is fully mediated (the coefficient is reduced and becomes statistically insignificant) (Model 6). Having a masters or a Ph.D. in STEM increases the propensity to be working in STEM by approximately 20 percentage points, while having an advanced degree in a non-STEM field reduces the likelihood of working in STEM by more than 20 percentage points. A cohort pattern emerges for computer science majors, with the most recent college cohorts being the most likely to work in STEM. Controlling for college cohort and advanced degree holding, however, has little impact on the gender/race gaps for computer science graduates working in STEM, as these coefficients remain relatively unchanged across models.

Adding controls for family characteristics (Model 8) does partially mediate the gender/race gaps among computer science majors in working in STEM. However, with all controls in the model, white women remain 12 percentage points less likely to work in STEM compared to white men. Black and Hispanic women are even less likely to work in STEM compared to their white, male counterparts, and Asian women remain 6 percentage points less likely to work in STEM. Including controls for family characteristics have virtually no impact on the likelihood of working in STEM for black, Hispanic, or Asian men relative to white men.

For both men and women, being married is positively associated with persisting in STEM, though cohabiting is negatively associated with persevering in STEM. Having children is also negatively associated with persisting in STEM, particularly when children are older (over the age of six). Interestingly, we find no gender differences in propensity to work in STEM associated with family characteristics among computer science graduates. Married and cohabiting women are equally likely to work in STEM as married men, as are women with children, although coefficients of the interaction among gender, cohabitation, and having children are slightly negative (though insignificant). This implies that among computer science degree holders, family characteristics do not appear to influence persistence in STEM differentially by gender.

8. Engineering Majors

The engineering story is quite different (Table 3). Among engineering degree-holders, women are approximately 3 percentage points less likely to work in STEM compared to men. As shown in Table 1, the female engineering degree holders were younger on average than the male engineering degree holders. Controlling for differences in age and the survey year actually *widens* the gender gap in STEM employment, since age is negatively correlated with persisting in STEM. Differentiating by race (Model 3), white, black, and Hispanic women are least likely to work in STEM compared to their white male counterparts. The gap for white women is 8 percentage points, while black women are 12 percentage points and Hispanic women are 10 percentage points less likely to work in STEM relative to white men. Asian women are no less likely to work in STEM relative to white men. Among the men, black and Hispanic men are less likely to work in STEM relative to white men, but Asian men are approximately 5 percentage points more likely to work in STEM.

In contrast to the story in computer science, foreign-born engineering majors are *less* likely to be working in STEM relative to native-born majors. Controlling for advanced degrees exacerbates the native-foreign born gap, suggesting that foreign-born engineering majors are less likely to obtain higher degrees in STEM. Again, a cohort pattern emerges for engineering majors, with the most recent college cohorts being the most likely to work in STEM.

Similar to the findings for computer science, we see little change in the gender/race gap in working in STEM with the inclusion of controls for college cohort, advanced degree holding in STEM, and the main effects for family characteristics. Only once we include interactions of our family characteristics with an indicator for female, allowing the family characteristics to have a different effect on the likelihood of working in STEM for men compared to women, do we see any change in the gender gaps in working in STEM (Model 8). Including controls for whether the women are married or cohabiting and have any children substantially reduces the gender gap in working in STEM among engineering majors. For white women, the gap shrinks from 8 to 3 percentage points, while reductions were quite similar in magnitude for the other racial groups as well. For white, black, and Hispanic women, observable characteristics can explain between 55% and 64% of the gender gap in persistence in STEM. For Asian women, controlling for observable characteristics actually reverses the gender gap in persistence in STEM: Asian women are 4 percentage points *more* likely to be working in STEM relative to white men.

In contrast to computer science, family characteristics *do* appear to have different associations with working in STEM for men and women engineering graduates. While we find no association between marriage and working in STEM for men (coefficient: 0.006 and insignificant), married women are 4 percentage points less likely to work in STEM compared to married men. Cohabiting women, however, are more likely to be working in STEM than cohabiting men, though the difference is not significant. Having any children is negatively associated with working in STEM for both men and women, but women with children are 4 percentage points less likely to work in STEM compared to men with children. This implies that married female engineers with children face substantially more barriers to working in STEM than do married male engineers who are parents.

These analyses reveal two distinct portraits of the gender gap in persistence in STEM for those majoring in computer science and engineering. Among computer science majors, women are substantially less likely to work in STEM compared to men, and observable characteristics do little to explain this gap. In contrast, among engineering majors, the gender gap in working in STEM is much smaller, and approximately half of the gender gap can be explained by observable characteristics: namely, family characteristics.

8.1. How Does Our Restricted Definition of "STEM" Affect Results?

To test the sensitivity of our results to the definition of "working in STEM", we also ran models where we restrict the definition of working in STEM to be "working in STEM occupation of same major". For instance, if the respondent obtained a bachelor's degree in computer science, then they will be considered "working in STEM" only if they also work in a computer science occupation. Among computer science degree holders, approximately 90% of those working in any STEM field were working in computer science. In contrast, engineering degree holders were less likely to be working in engineering occupations: 75% of engineering degree holders working in any STEM field were working in engineering occupations. An additional 15% of those working in any STEM field were working in computer science (see Table A1).

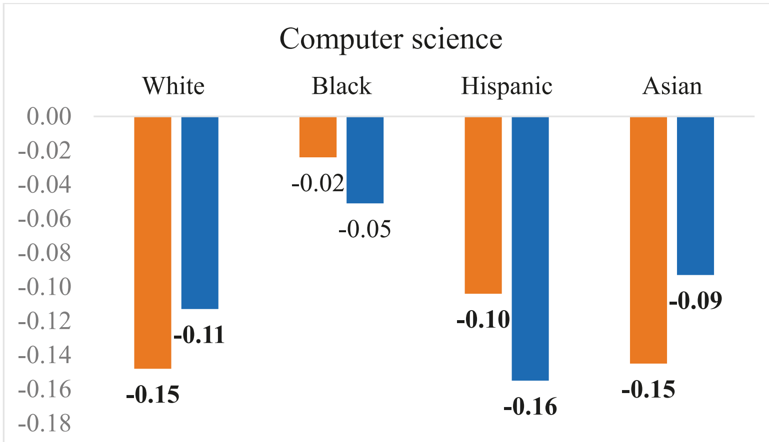
Using our restricted definition of working in STEM does not alter results much among computer science degree holders (see Table A2). This is not surprising, since 90% of those working in any STEM occupation were working within their field of major. Gaps are slightly smaller for all racial groups aside from Asian women, and, once again, controls do very little to alter the gender gap in persistence in STEM.

The gender gap in persisting in STEM among engineering degree holders also does not change upon using a more restricted definition of working in STEM, except for Asian men and women. While Asian men and women were actually *more* likely to work in STEM compared to white men using a traditional definition of working in STEM (including any STEM occupation in the four main fields of STEM), restricting the definition to only include engineering occupations reverses the direction of the relationship. In the fully-controlled model, both Asian men and women were 8 percentage points *less* likely to work in engineering compared to white men. Upon further exploration, this result is due to Asian men and women with engineering degrees having a higher propensity to work in computer science compared to non-Asian engineering degree holders.

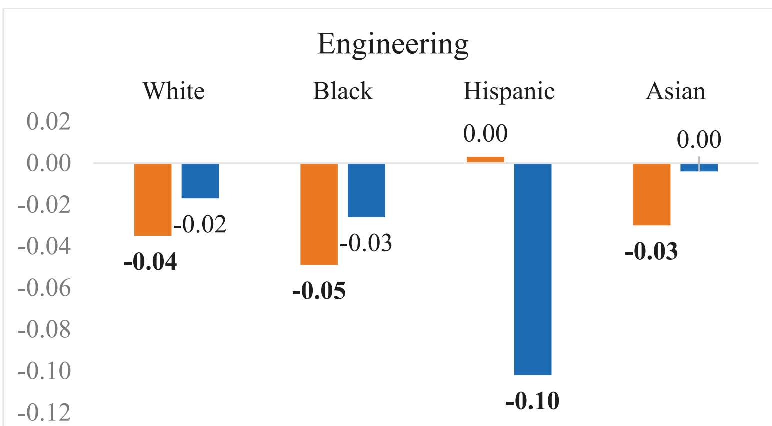
There is considerable heterogeneity among engineering graduates. Because it remains among the engineering fields with the lowest representation of women (Michelmore and Sassler 2016), some have suggested that electrical engineers are more similar to computer science majors than to many other engineering fields (like mechanical or civil engineering). We therefore explored whether grouping electrical engineers with computer science graduates altered our results substantively. Analyses run on our new, expanded group (computer science and electrical engineering graduates) reveal more similarities between electrical engineers and computer science graduates than other engineering specializations. For this new expanded category the gender and race gaps in STEM employment are accentuated, and family characteristics now largely do not mediate the gender/race gaps evident for those working in STEM. In contrast, the omission of electrical engineering majors from the engineering models results in smaller gaps in STEM employment among our more constrained group of engineers, and family characteristics now fully mediate the gender and race gaps in STEM employment. Our results indicate that not all engineers are alike; the barriers facing women engineering graduates who specialized in electrical engineering—an area with relatively few women—are more similar to those experienced by women in computer science than they are to women in other engineering disciplines.

8.2. Differences by Race/Ethnic Group

Our analyses in Tables 2 and 3 measure gender and race gaps relative to white men; estimating within-race gender gaps in likelihood of working in STEM separately for each of the four main race/ethnic groups presents a similar story (see Figure 3). Figure 3 presents results from regressing an indicator for working in STEM on an indicator for whether the respondent is female for each of the four main race/ethnic groups, measuring how gender gaps change with the addition of the full set of controls from Model 8 in Tables 2 and 3 (the dark bar represents the coefficient without controls, while the light bar represents coefficients with controls). In computer science, we find evidence that observed characteristics explain more of the gender gap in working in STEM for white and Asian computer science degree holders than for black and Hispanic degree-holders. With no other controls in the model, white women are approximately 15 percentage points less likely to work in STEM relative to white men. This gap narrows to 11 percentage points with the addition of controls for educational attainment, college cohort, and family characteristics. Similarly, Asian women are approximately 15 percentage points less likely to work in STEM relative to Asian men. Including the full set of controls, this gap narrows to 9 percentage points. The story is quite different for black and Hispanic computer science degree-holders. Among black computer science degree-holders, we find no statistically significant differences in the likelihood of working in STEM between men and women in either model. Among Hispanic degree-holders, we find evidence that including controls for demographic characteristics *exacerbates* the gender gap in persisting in STEM occupations—increasing the gap from 10 to 16 percentage points with the inclusion of controls.



(**a**)



(**b**)

Figure 3. Differences in likelihood of working in STEM for women relative to men by race, coefficient on indicator for women from LPM regressions predicting likelihood of working in STEM, separate regressions by race/ethnic group and STEM major. (**a**) Computer Science Majors; (**b**) Engineering Majors. Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, and employed at the time of survey. Bolded coefficients indicate statistically significant at $p < 0.05$ level.

Among white, black, and Asian engineering degree-holders, the race-specific gender gaps in STEM persistence are consistent with the overall results. For these three groups, women are between 3 and 5 percentage points less likely to work in STEM relative to their male counterparts, not including any controls in the model aside from age and survey year. Including the full set of controls presented in Model 8 in Table 3, fully mediates the gender gaps in likelihood of working in STEM for these groups. This implies that among engineering graduates, the majority of the gender gap in propensity to work in STEM is explained by difference in observable characteristics between men and women. Among Hispanics, we see a different pattern. Similar to Hispanic computer science degree holders, we find that including controls for observable characteristics actually exacerbates the gender gap in propensity to work in STEM, increasing from virtually no gap in the uncontrolled model, to 10 percentage points in the fully-controlled model.

8.3. How Has the Gender Gap in Employment in STEM Changed over Time?

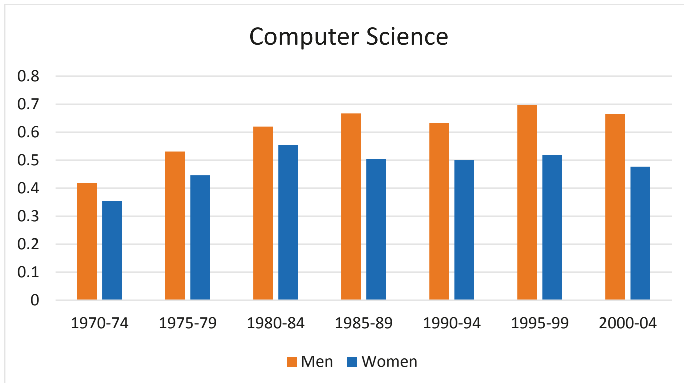
The gender and racial composition of computer science and engineering majors have shifted dramatically over the last several decades (see Figure 1). Since the 1970s, white women have exhibited a retreat from computer science, accounting for 28% of computer science majors during 1970–1974, to just 16% of majors among the 2000–2004 graduating cohort. The decline of women's representation in computer science would be more dramatic, were it not for the increase in representation among minority women. In engineering, women have increased both their representation and become more diverse. With these large demographic shifts in computer science and engineering, it raises the question of how the gender gap in working in STEM has changed over time.

To answer this question, we predict the probability of working in STEM separately for men and women for each cohort using a regression similar to Model 8 in Tables 2 and 3, but adding an interaction term of college cohort and gender, to allow for the gender gap in STEM employment to change over cohort (see Figure 4). We hold all other characteristics at their mean value. The predicted probabilities indicate how the gender gap in working in STEM has changed by college degree cohort. In computer science, we find that the decline of white female majors over the last several decades coincides with a retreat of women from working in STEM as well. Relative to their male counterparts, women who have graduated from college since 1985 have a much lower predicted probability of working in STEM than men who graduated from college during the same time period (ranging from a 12 to 19 percentage point difference). This analysis is conditional on obtaining a college degree in computer science, and implies that on top of being less likely to major in computer science to begin with, women who graduated with degrees in computer science over the last two decades are also less likely to work in STEM.

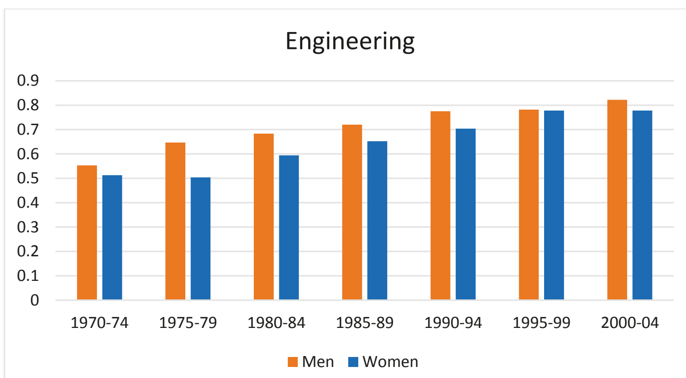
In engineering, on the other hand, we find the opposite pattern by college cohort. Since 1975–1979, the gap in working in STEM between women and men who graduated with an engineering degree has narrowed such that, for the college cohort 1995–1999, the predicted probabilities of working in STEM are identical. This narrowing of the gender gap in STEM employment has occurred at the same time that more women have obtained engineering degrees.

Finally, we also examined whether major non-demographic factors influencing the likelihood of working in STEM persist among the most recent cohorts. To do that, we ran our linear probability models, but limited our sample to the two most recent cohorts—those who graduated between 1995 and 1999, and those finishing their degree between 2000 and 2004. The general patterns shown in Table 2 for computer science remained, but the gender and race gaps were considerably larger (results not shown). Among the most recent cohorts, female computer science graduates were considerably less likely to be working in STEM jobs than their male counterparts, and the gaps between white and Hispanic females and white males had expanded, though Asian women who had completed a degree in computer science were no less likely than their White male counterparts to be working in STEM jobs. Our measures of family status (married and had any minor children) was also not significant among the most recent cohorts of computer science graduates, perhaps due to delayed marriage and parenting among both women and men.

Among engineering graduates, on the other hand, gender disparities in employment were far narrower among more recent cohorts. Nonetheless, we do observe some widening of disparities among racial minorities (results not shown). The gender gap between white women and men remains largely the same magnitude, even as their representation in engineering grew. The gap between Black and Hispanic women and men, relative to white men, is greater among the two most recent cohorts of engineering graduates. Furthermore, the employment advantage demonstrated by Asians is no longer significant among the two most recent cohorts, though in the full sample both Asian women and men had exhibited a greater probability of working in STEM jobs than had white males. However, our family covariates do not explain the gender and race gaps in employment among the most recent cohorts, as the race gaps persist upon including our family controls.



(**a**)



(**b**)

Figure 4. Predicted Probabilities of Working in STEM by College Cohort for Women and Men. (**a**) Computer Science Majors; (**b**) Engineering Majors. Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, and employed at the time of survey.

9. Discussion and Conclusions

Much progress has been made in diversifying the STEM labor force over the last several decades (Xie and Killewald 2012), but women continue to remain underrepresented in science and engineering occupations. Numerous studies have examined the source of the gender gap in women's STEM presence, noting differences in major field of study, transitions into STEM occupations, as well as differential retention in STEM occupations, working patterns, and the challenging experience of being a minority. Restricting our sample to STEM degree holders in computer science and engineering eliminates some potential factors, such as differences in human capital accumulation or employment opportunities that contribute to women's underrepresentation. We use SESTAT data and assess the factors that influence the gender gap in persistence in STEM employment in computer science and engineering occupations, assessing differences by race as well as changes in the gender gap across cohorts.

We find sizable and significant gender and race gaps in STEM employment for both computer science and engineering degree holders. Disparities were greater, however, in computer science than in engineering. Women who received degrees in computer science were approximately 14 percentage points less likely to work in STEM occupations than white men, while women in engineering were 7 percentage points less likely to do so. Black and Hispanic men were also significantly less likely to be working in STEM occupations than their white male counterparts in both fields, but the gap was generally smaller than it was for women. Contrary to our expectations, we find no evidence that the gender gap in employment is narrowing among more recent college graduates, at least when it comes to employment in computer science occupations. Even though female employment throughout the life course has become increasingly normative in American society, and computer science jobs have proliferated and generally provide good wages, the occupation is not succeeding in drawing women. Instead, the evidence suggests that something about the field of computer science is repelling rather than attracting women.

However, it is difficult to account for the factors associated with these employment disparities. We found little evidence that differences in observable characteristics between men and women could explain the gender gap in persisting in STEM among computer science degree holders, contrary to our hypotheses. After controlling for college cohort, advanced degree holding, and marriage and family formation, white women with computer science degrees remained 12 percentage points less likely to work in STEM compared to white men. This suggests that there remain unobserved barriers to working in STEM for female computer science majors relative to male computer science majors. Empirical evidence suggests that computer science education is less welcoming to female students (Cheryan et al. 2013; Master et al. 2016) and that the field is often viewed as a quintessentially masculine subject (DuBow and James-Hawkins 2016), especially by men (Corbett and Hill 2015; Smyth and Nosek 2015). Furthermore, anecdotal evidence suggests that such barriers persist, or are even exacerbated, among those working in computer science occupations (Margolis and Fisher 2001; Mundy 2017), resulting in high attrition of women from jobs in computer science.

In engineering, we find a different story. Gender gaps in persisting in STEM were smaller than in computer science, and about half of the gap could be attributed to differences in the characteristics of male and female engineering degree holders. This is consistent with the changing demographic patterns that have occurred in these two fields over time. Women have historically obtained a greater proportion of degrees in computer science but are less likely to major in computer science today than they were forty years ago. In computer science, therefore, the demographic characteristics of men and women are quite similar. Engineering, in contrast, has seen a dramatic increase in women's their representation among degree holders in recent years, and therefore differ more in terms of their demographic characteristics: the female engineering degree holders are much younger, much less likely to be married, and much less likely to have children compared to the male engineering majors. Over time, then, as older engineering degree holders, who are predominantly male, retire, gender disparities in demographic characteristics—as well as retention in STEM occupations associated with engineering—should narrow.

Many attribute the dearth of women in STEM occupations to the challenges women (but not men) face in attempting to balance what are often rigid employment expectations with family life. Our findings suggest that the associations between family life and employment are more nuanced than one would expect. Among computer science degree holders, men and women were equally (un)likely to be married and have minor children. Our regression analysis suggests that both men and women were *more* likely to be working in STEM if they were married, relative to those who were single. Similarly, the presence of children reduced the propensity to work in STEM among both men and women equally, although having young children (under the age of six) was not significantly associated with working in STEM relative to childless individuals. In computer science, therefore, family characteristics do not appear to be an obstacle for women more so than men. That is the case, at least, among those who remained in computer science jobs. Evidence from other studies have suggested that those for whom children are not a deterrent in the work force, and who can maintain employment and even earn higher wages when they are parents of young children, are highly selective (e.g., Michelmore and Sassler 2016; Pal and Waldfogel 2016; Buchmann and McDaniel 2016). Furthermore, given that these women are better represented among those graduating in the 1980s than the 1990s and into the 21st century, they are older, may be more likely to be divorced or to have older children.

Family life, however, appears more challenging to adjudicate for women engineers than for their male counterparts. Among engineering majors, observed differences in the propensity to be married (75% of men were married compared to only 63% of women) and to have minor children (52% versus 44%, respectively) translate into differences in the likelihood of working in STEM. While married men in engineering were no less likely to be working in STEM compared to single men, married women were 4 percentage points less likely to be working in STEM relative to married men. Furthermore, having children further exacerbated this gender gap. Even though having minor children reduced the likelihood of working in STEM for both men and women, women with minor children were significantly less likely to work in STEM compared to men with children (by 4 percentage points). These results are consistent with the idea that women in engineering face barriers in balancing work and family that do not prevent men from combining marriage and family with working in STEM. Of note is that those with preschool aged children were slightly more likely to be working in engineering jobs, and that this effect does not differ for men and women. Perhaps it is not the presence of children, per se, that challenges employment among those in STEM jobs, but differences in the availability of full-day and full-year care for children of differing ages. Finally, there appears to be heterogeneity among engineering occupations, with electrical engineering looking more akin to computer science in its gender representation and the gender employment gap than to other engineering specialties. Such findings reveal the challenges that remain to making STEM fields where women are highly underrepresented welcoming workplaces.

In examining how these patterns have changed over time, computer science appears to be the exception to increasing female representation, as recent cohorts of female computer science majors are increasingly *less* likely to work in STEM jobs than their counterparts who graduated three decades ago. Women and men are equally likely to work in STEM jobs if they graduated in the 1970s and 1980s. We document an emerging gender gap in employment in computer science in the late 1980s, rising to between 10 and 15 percentage points in the more recent cohorts. The declining share of women and minority computer science workers has been well canvassed in the popular media (Dewey 2014; Mundy 2017; Stross 2008). Our findings shed additional light on the need to better understand the factors contributing to women's diminishing representation in this field, given that computer science is of considerable importance to the American and global economy. While our findings do not provide much purchase on *why* women find computer science an unwelcome field, our results are consistent with several recent studies detailing persistent wage gaps between men and women in computer science (Michelmore and Sassler 2016). Increasing the representation of women in computer science employment, then, appears to be very challenging, and additional research is needed to best determine effective ways of addressing gender barriers to retention.

Our study is not without limitations. The nature of our data does not allow us to determine the factors that push or pull men or women out of the STEM labor force and into other occupations, or whether this process differs for men and women. Recent research has suggested that women exit particular STEM fields as a result of frustration with working conditions (e.g., Glass et al. 2013; Hunt 2016), such as dissatisfaction with pay and promotion opportunities. Despite the increasing presence of women in STEM fields of study, the evidence indicates that women are significantly less likely to be retained in the STEM labor force (Glass et al. 2013). In engineering, however, we find no evidence of an expanding gender gap in employment over time, coinciding with an increase in women majoring in engineering. Nonetheless, family responsibilities more adversely shape women engineering graduates' odds of retention than they do for men, suggesting the need to further explore how spousal and parental roles play out differentially in the spheres of work and home.

Over the past few decades, remarkable progress has been made in narrowing the gender gap in STEM employment, but considerable work remains. While the engineering field presents a reason for optimism that women's persistence in STEM will increase as their representation among majors continues to rise, the story in computer science is just the opposite. Increasing women's representation in the two largest STEM fields has important implications for gender equity in the labor force, as well as the overall gender wage gap. Computer science and engineering are among the highest-paying fields for college graduates; expanding women's presence in these fields would go a long way towards reducing gender inequality in pay.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. List of STEM occupations and the fraction of computer science and engineering STEM workers working in each occupation.

STEM Occupations	Percent of Computer Science STEM Workers	Percent of Engineering STEM Workers
Computer and information scientists	66.7%	15.7%
Mathematical scientists	7.0%	<1%
Postsecondary teachers—computer and math sciences	16.0%	<1%
Agricultural and food scientists	<1%	<1%
Biological and medical scientists	1.0%	1.0%
Environmental life scientists	<1%	<1%
Postsecondary teachers—life and related sciences	<1%	<1%
Chemists, except biochemists	<1%	<1%
Earth scientists, geologists and oceanographers	<1%	<1%
Physicists and astronomers	<1%	<1%
Other physical and related scientists	<1%	<1%
Postsecondary teachers—physical and related sciences	<1%	<1%
Aerospace, aeronautical, or astronautical engineers	<1%	5.9%
Chemical engineers	<1%	6.2%
Civil, architectural, or sanitary engineers	<1%	12.0%
Electrical or computer hardware engineers	2.5%	17.7%
Industrial engineers	<1%	5.1%
Mechanical engineers	<1%	15.2%
Other engineers	1.4%	13.4%
Postsecondary teachers—engineering	<1%	3.9%
Percent working in STEM occupation of same major	89.7%	73.6%
Top occupations for individuals not working in STEM		
Science and Engineering Managers	14.0%	26.1%
Science and Engineering pre-college teachers	13.6%	1.7%
Science and Engineering technicians	19.1%	11.9%
Sales and marketing occupations	8.6%	11.3%
Other non S&E occupations	16.8%	22.7%

Table A2. Linear probability models predicting working in a computer or math science occupation: Computer science degree holders.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Survey Year			0.009	***	0.008	***	0.008	***	0.001		0.002		0.002	*	0.002	*
Age			−0.007	***	−0.007	***	−0.007	***	−0.001		0.0002		0.0002		0.0002	
Gender and race																
Female	−0.123	***	−0.123	***												
White female					−0.131	***	−0.132	***	−0.130	***	−0.120	***	−0.119	***	−0.110	***
Black female					−0.133	***	−0.136	***	−0.145	***	−0.130	***	−0.125	***	−0.115	***
Hispanic female					−0.162	***	−0.186	***	−0.200	***	−0.172	***	−0.169	***	−0.161	***
Asian female					−0.046	***	−0.099	***	−0.090	***	−0.080	***	−0.080	***	−0.070	***
White male (ref)																
Black male					−0.105	***	−0.114	***	−0.123	***	−0.106	***	−0.104	***	−0.104	***
Hispanic male					−0.074	***	−0.092	***	−0.098	***	−0.073	***	−0.071	***	−0.072	***
Asian male					0.099	***	0.047	***	0.056	***	0.0356	**	0.035	**	0.035	**
Foreign-born							0.068	***	0.057	***	0.017		0.016		0.016	
BA cohort (ref: 1970–1974)																
1975–1979									0.098	***	0.093	***	0.100	***	0.100	***
1980–1984									0.184	***	0.169	***	0.177	***	0.176	***
1985–1989									0.216	***	0.208	***	0.212	***	0.212	***
1990–1994									0.205	***	0.203	***	0.204	***	0.203	***
1995–1999									0.264	***	0.262	***	0.620	***	0.262	***
2000–2004									0.264	***	0.258	***	0.259	***	0.259	***
Advanced degrees (ref: BA only)																
STEM master's											0.174	***	0.172	***	0.172	***
STEM PhD											0.132	***	0.131	***	0.132	***
Non-STEM advanced degree											−0.222	***	−0.223	***	−0.224	***
Marriage and family																
Married													0.020	**	0.014	
Cohabiting													−0.043	*	−0.019	
Has kids													−0.041	***	−0.036	***
Has kids under 6													0.025	**	0.039	***
FemaleXMarried															0.013	
FemaleXCohabiting															−0.073	
FemaleXHas kids															−0.013	
FemaleXHas kids under 6															−0.042	*
R-squared	0.013		0.033		0.04		0.042		0.051		0.094		0.095		0.095	
N	15,895		15,895		15,895		15,895		15,895		15,895		15,895		15,895	

Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, who are employed at the time of the survey. Notes: Results from linear probability model regressing an indicator for working in STEM on indicator for female and demographic characteristics. Women with children are defined as those who have at least one child under the age of 18 living in the household. Marriage and cohabitation evaluated at the time of the survey. Regressions weighted by person weights. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table A3. Linear probability models predicting working in an engineering occupation: Engineering degree holders.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Survey Year		−0.006 ***	−0.005 ***	−0.004 ***	−0.015 ***	−0.014 ***	−0.013 ***	−0.013 ***
Age		−0.007 ***	−0.008 ***	−0.007 ***	0.002 ***	0.002 ***	0.002 ***	0.002 ***
Gender and race								
Female	−0.039 ***	−0.065 ***						
White female			−0.057 ***	−0.055 ***	−0.052 ***	−0.051 ***	−0.050 ***	0.005
Black female			−0.115 ***	−0.108 ***	−0.108 ***	−0.087 ***	−0.086 ***	−0.043
Hispanic female			−0.087 ***	−0.056 **	−0.063 **	−0.063 ***	−0.064 **	−0.011
Asian female			−0.193 ***	−0.129 ***	−0.124 ***	−0.140 ***	−0.143 ***	−0.080 ***
White male (ref)								
Black male			−0.041 ***	−0.023	−0.032 **	−0.035 **	−0.034 **	−0.033 **
Hispanic male			−0.043 ***	−0.010	−0.019 *	−0.011	−0.010	−0.010
Asian male			−0.137 ***	−0.068 ***	−0.065 ***	−0.082 ***	−0.083 ***	−0.083 ***
Foreign-born				−0.086 ***	−0.082 ***	−0.106 ***	−0.105 ***	−0.105 ***
BA cohort (ref: 1970–1974)								
1975–1979					0.064 ***	0.056 ***	0.058 ***	0.058 ***
1980–1984					0.074 ***	0.069 ***	0.073 ***	0.073 ***
1985–1989					0.097 ***	0.084 ***	0.088 ***	0.088 ***
1990–1994					0.165 ***	0.150 ***	0.153 ***	0.152 ***
1995–1999					0.238 ***	0.210 ***	0.211 ***	0.210 ***
2000–2004					0.376 ***	0.334 ***	0.335 ***	0.331 ***
Advanced degrees (ref: BA only)								
STEM master's						0.090 ***	0.090 ***	0.090 ***
STEM PhD						0.113 ***	0.113 ***	0.112 ***
Non-STEM advanced degree						−0.242 ***	−0.241 ***	−0.243 ***
Marriage and family								
Married							0.008	0.019 ***
Cohabiting							−0.058 ***	−0.055 ***
Has kids							−0.012 *	−0.009
Has kids under 6							−0.005	−0.004
FemaleXMarried								−0.067 ***
FemaleXCohabiting								−0.018
FemaleXHas kids								−0.026
FemaleXHas kids under 6								−0.003
R-squared	0.006	0.024	0.034	0.037	0.047	0.0855	0.086	0.0864
N	43,266	43,266	43,266	43,266	43,266	43,266	43,266	43,266

Source: National Science Foundation's Scientists and Engineers Statistical Data System (SESTAT) 1995–2008. All men and women graduating with a bachelor's degree in computer science or engineering between 1970 and 2004, who are employed at the time of the survey. Notes: Results from linear probability model regressing an indicator for working in STEM on indicator for female and demographic characteristics. Women with children are defined as those who have at least one child under the age of 18 living in the household. Marriage and cohabitation evaluated at the time of the survey. Regressions weighted by person weights. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

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Article

Gender in Engineering Departments: Are There Gender Differences in Interruptions of Academic Job Talks?

Mary Blair-Loy [1,*], Laura E. Rogers [1], Daniela Glaser [2], Y. L. Anne Wong [3], Danielle Abraham [4] and Pamela C. Cosman [5]

1 Department of Sociology, University of California, San Diego, La Jolla, CA 92093, USA; l1rogers@ucsd.edu
2 Department of Chemical Engineering and Materials Science, University of Southern California, Los Angeles, CA 90007, USA; dglaser@usc.edu
3 Department of Sociology, University of California, Santa Barbara, Santa Barbara, CA 93106, USA; ylawong@umail.ucsb.edu
4 Lindamood-Bell Learning Processes, 445 Marine View Ave #290, Del Mar, CA 92014, USA; danielle.abraham@lindamoodbell.com
5 Department of Electrical and Computer Engineering, University of California, San Diego, La Jolla, CA 92093, USA; pcosman@ucsd.edu
* Correspondence: mblairloy@ucsd.edu

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Abstract: We use a case study of job talks in five engineering departments to analyze the under-studied area of gendered barriers to finalists for faculty positions. We focus on one segment of the interview day of short-listed candidates invited to campus: the "job talk", when candidates present their original research to the academic department. We analyze video recordings of 119 job talks across five engineering departments at two Research 1 universities. Specifically, we analyze whether there are differences by gender or by years of post-Ph.D. experience in the number of interruptions, follow-up questions, and total questions that job candidates receive. We find that, compared to men, women receive more follow-up questions and more total questions. Moreover, a higher proportion of women's talk time is taken up by the audience asking questions. Further, the number of questions is correlated with the job candidate's statements and actions that reveal he or she is rushing to present their slides and complete the talk. We argue that women candidates face more interruptions and often have less time to bring their talk to a compelling conclusion, which is connected to the phenomenon of "stricter standards" of competence demanded by evaluators of short-listed women applying for a masculine-typed job. We conclude with policy recommendations.

Keywords: gender; STEM; interruptions; job talks; gender bias; faculty hiring; underrepresentation of women; women in science; double standards; stricter standards

1. Introduction

Women remain starkly under-represented in STEM (Science, Technology, Engineering, and Mathematics) professional occupations in the United States. Over the past two decades, researchers and policy makers have focused on "leaky pipelines" and challenges to the recruitment and retention of girls and women in STEM education, and women have made some gains there. However, women with college and advanced degrees remain underrepresented in many STEM fields [1,2]. Policy makers and academics view the paucity of women in academic STEM as placing limits on scientific creativity [3,4] and contributing to the national shortage of STEM professionals [5–7].

This paper focuses on tenured and tenure-track academic engineering faculty positions in research-focused universities [8–10]. The ways that gendered barriers may persist in academic hiring are not fully understood. Experimental studies have found that women can be held to double standards and stricter standards compared to men [11,12], especially when the highest levels of competence are demanded [13,14]. In contrast, another study that distributed a set of hypothetical short lifestyle descriptions of faculty job candidates without details of technical qualifications found that women had a higher chance than men of being chosen [15].

However, there is a dearth of research regarding how the faculty hiring process unfolds within real departmental contexts. Moreover, we are aware of no study that considers whether gender barriers are salient for women and men who have risen to the top of a large applicant pool and been added to the "short list" of finalists invited for a campus interview.

We analyze this issue with a case study of short-listed applicants, who have been invited to campus to interview for tenure-track faculty appointments within five male-dominated engineering departments across two Research 1 universities.[1] Case-oriented research is not intended to be generalizable but rather sheds light on under-studied social processes. Our data come from the most important segment of the job interview: the "job talk", a seminar in which the candidate presents his or her original research to the academic department. Our paper assesses whether in these talks, women candidates face greater scrutiny and stricter standards, manifesting as more questions, compared to men candidates.

We analyze the number of questions presenters receive from the audience, which is mostly composed of department faculty and graduate students. By asking questions, faculty try to assess whether the candidate is fully in command of his or her research project and its larger implications. Some interruptions may indicate audience engagement, while others may indicate that the speaker was unclear or that the audience questions the presenter's competence.

To preview our results, we find that compared to men presenters, women face more questions during their job talk seminars, are confronted with more follow-up questions, and spend a higher proportion of time listening to audience speech. Moreover, we find that questions directed to women and men candidates are more prevalent in more highly male-dominated departments, compared to departments that have a somewhat higher proportion of women on the faculty. More senior candidates generally receive fewer questions than more junior ones, but women face more questioning and scrutiny compared to men with the same level of experience.

As noted in the conclusion section, our data have some limitations. Our IRB agreement allows us research access to this treasure trove of video recordings collected for other purposes but does not permit us to examine which candidates were actually offered a job. Even if job offer data were available, it would be of limited value. Many candidates withdraw from consideration after receiving preferable offers from other universities, so the absence of an offer does not reliably indicate a candidate's lack of success with the interview. The data do show that, regardless of gender, the number of questions is correlated with candidates' statements and actions indicating they are rushing to finish their slides and conclude their talk. To our knowledge, this is the first study of whether there are gender differences in the degree to which faculty candidates are interrupted during job talks.

The next section will present our theoretical framework, which motivates our research questions. We adopt the broad sociological perspective that gender frames expectations and interactions within academic departments. We briefly present literature on implicit biases, which automatically give men more credit than similar women for competence. We then examine how these processes can unfold in ways consistent with double or stricter standards, which could manifest as evaluators posing

[1] Each university is an elite research-focused institution, ranked as a "Highest Research Activity" university in the Carnegie Classification of Institutions of Higher Education and has an engineering school ranked among the top 50.

more questions during the job talk. We therefore turn to insights from a literature on interruptions in workplace or task-oriented interactions.

Following that, we present our data and methods. Next, we provide descriptive and multivariate results. Our discussion and conclusion section also presents study limitations and policy implications.

2. Theoretical Framework and Research Questions

Extensive research documents broadly shared implicit biases, which can automatically filter assessments of professionals in ways that penalize women, while giving men automatic credit for competence [16–18]. Assumptions that women are less competent are particularly prevalent in male-dominated settings [14,19,20]. This is important in our case study. Engineering has historically been seen as a "masculine" profession, because it is numerically male-dominated, and because the culture and ethos of the industry are considered masculine [21,22]. Further, in male-dominated disciplines such as engineering, academic success has been understood to depend on raw brilliance, a quality less frequently attributed to women [23].

The processes of biased evaluation are illuminated by studies of how, under the illusion of meritocracy, evaluators can apply double standards in evaluation and hiring. Studies of academic hiring, based on detailed candidate information that is real or believed to be real by faculty evaluators, discover that women candidates are seen as less competent, less qualified, and less hirable, compared to men with similar qualifications. In an analysis of real candidate applications selected for a prestigious medical research fellowship, faculty evaluators gave women applicants less credit than men for their publications [24]. In a study of psychology professor applications, faculty assessing one ostensibly real CV with a female name gave this candidate less credit for her qualifications and were less likely to recommend hiring her, compared to other participants, who viewed an identical CV with a male name [25]. Another experimental study used physics, chemistry, and biology professors as participants to examine an ostensibly real CV of either a man or a woman science student applying for a lab manager position [26]. Compared to equally qualified women candidates, the men were more likely to be rated as competent and hirable and were offered a higher salary.

A line of experimental research by Foschi and colleagues examines how subjects evaluating results of participants' simulated tasks are implicitly aware of status characteristics such as gender. These studies show that evaluators generally hold women to more scrutiny and harsher standards in the inference of competence. In contrast, they will tend to assess similar performances by men with more lenient standards and give them the benefit of the doubt [11,12,14]. Particularly when tasks are seen as masculine, evaluators generally assume that the man candidate has more ability than a comparable woman and apply more lenient standards for him than for her [14].[2]

In contrast to the broad direction of the literature cited above, one study found that evaluators were more likely to rate a woman academic candidate than a man academic candidate as hirable [15]. However, this study relied on short narrative summaries of similarly strong men and women candidates. Importantly, the narrative summaries described a hypothetical search committee's evaluations of the job candidates, and assigned the hypothetical men and women candidates identical numerical scores for their interviews and job talks.[3] The provision of only narrative summaries and secondary judgments allows evaluators to rely on others' assessments of the job candidates instead of forming their own judgment about the hypothetical candidates based on detailed objective information generally provided in academic job searches, such as education credentials and research productivity, alongside any implicit gender biases that may exist. Moreover, the assignment of identical

[2] Foschi's ([11], p. 31) review of experimental research shows "substantial support" for these predictions.
[3] A third, weaker candidate was added as a foil.

scores obviates the double standards phenomenon that the literature shows generally favors men in masculine-typed occupations.[4]

In other research, Biernat and Kobrynowicz [13] found that for inferences of minimum ability, lower standards are set for the lower status group (such as women) and higher standards are set for the higher status group (men). However, when inferences about *greater ability* had to be made, the reverse pattern emerged. Women were held to stricter standards and men to more lenient standards. Similar results were found in other studies (see [11] for review, e.g., [27]). Further, women were similarly or more likely to be considered competent enough to be short-listed when compared to the lower standards generally set for women but they were held to harsher standards in objective rankings as well as in promotion and hiring decisions [28,29].

Thus, scope conditions for double standards becoming stricter standards and greater scrutiny for women include masculine-typed settings when confirmatory decisions (that require higher assessments of ability) are being made. These scope conditions fit our study.

Overall, this line of research suggests that in an actual engineering faculty job search, with real stakes and zero-sum decisions involved, women who have made it to the short list may confront heavier scrutiny and stricter standards than short-listed men during the interview. This reasoning suggests that women job candidates may be implicitly assumed to be less competent, will be challenged more than men candidates and face more questions by faculty members during their job talk. Patterns of evaluators' closer scrutiny and stricter standards for women are manifestations of "prove it again" bias [18]. More broadly, by studying audience—candidate interactions in recorded job talks, we assess whether gender barriers emerge within the social context of actual departments as work units and if such barriers vary depending on social structural features of departments [30].

We now turn specifically to the literature on interruptions. Here, this literature will help us formulate specific research questions. Later, we return to the interruptions literature as we operationalize questions and interruptions.

The literature on conversational interruptions abounds with examples of gender effects. The classic study by Zimmerman and West [31] found that men interrupt women more than the other way around. One experimental study of task-oriented groups found that the odds of a man interrupting another man are less than half of the odds that a man will interrupt a woman. Further, men's interruptions of men are generally more positive and affirming, while men's interruptions of women are more negative. In contrast, women interrupt women and men equally [32]. Fewer interruptions were found in all-male groups than in mixed-gender or all-female groups [33].

Other studies have found that a host of variables are predictive of interruptions, and may be more significant than gender in particular situations. For example, Irish and Hall [34] found that patients interrupt more than their physicians do, but also patients tend to interrupt with statements whereas physicians interrupt by asking questions. In conversations between managers and employees, Johnson [35] found that "formal legitimate authority severely attenuates the effect of gender in these groups". While authority, status, topic, setting, group size and composition, and many other factors have been shown to play significant roles in predicting conversational interruptions, considerable research has supported the basic gender effect that men interrupt more than women do [36–38], and that women are more frequently interrupted than men [32,39].

These studies on gender and implicit bias, double standards and interruptions motivate our research questions.

RQ1a: Among job candidates, do women experience more questions than men?
RQ1b: Relative to men, is a higher share of women's candidate time taken up by audience speech?

[4] Williams and Ceci [15] supplemented the study of narratives (they received 711 evaluations) with "control studies" on small groups of hypothetical CVs. In the male-dominated field of engineering, they sent out the hypothetical applicant CVs to only 35 faculty.

We also examine variation by department. Studies of gender in other workplace settings find that women face more equal treatment when they are in gender-integrated work settings, even within male-dominated occupations and industries [40,41]. As we explain below, the proportion of women among the faculty in the departments we study ranges from 4% to 18%. Although none of our departments are gender-balanced, the departments at the higher end are among those with the largest share of women faculty among the top 50 engineering schools in the nation. We study whether higher share of women in the departmental faculty is associated with fewer interruptions at the job talks in those departments.

RQ2: Net of gender, do candidates presenting in departments with a smaller proportion of women on the faculty experience more questions than candidates presenting in departments with a larger proportion of women on the faculty?

Further, we are interested in whether the job candidate's post-Ph.D. experience matters. Previous research on faculty CVs suggests that gender bias is more pronounced when candidates are more junior, and their potential is judged more subjectively, compared to when candidates are more senior and have a clear and unambiguous track record of achievement [25]. Moreover, in the interruptions literature, authority dampens the effect of gender on conversational interruptions [35].

RQ3: Do junior candidates experience more questions than more senior candidates?

3. Data and Methods

Case-oriented research identifies a small, non-random sample and investigates it deeply; this is not meant to be generalizable but rather illuminates the complexity of the context under study [42–44].[5] For our case study, we analyze interruptions in job talks in highly ranked engineering departments, in order to examine whether gendered processes unfold despite formal commitments to meritocracy and fairness.

3.1. Data

Our data of 119 recorded job talks come from five departments across two Universities, whose engineering divisions each rank in the national top 50.[6] The departments are Computer Science (CS), Electrical Engineering (EE), and Mechanical Engineering (ME). CS and EE are studied at both University 1 and University 2. ME is only considered at University 1. The share of women on the faculty ranges from 4% to 18%. We analyze 92 talks from University 1 and 27 from University 2.

The talks existed as archived videos that were already recorded by departments during two years of hiring, for purposes unrelated to this study. Some departments want to have recordings for faculty who are out of town to be able to evaluate the candidate's talk. Other departments wish to have the recordings available as a resource for their graduate students.

In our data, the job talks take place in a campus conference room. The candidate is evaluated on his or her performance in presenting their original research and responding to questions. All departments in the study schedule job talks for nominally one hour. Candidates are given their schedules in advance. Both candidates and audience members generally also know that there is no hard stop at the one-hour mark, since running over will merely subtract some minutes from the next event, which is typically lunch, or a break.

[5] Many high impact studies of social inequality have a case study design. These include Armstrong and Hamilton [45], Hochschild [46], Castilla [47], Cech and Waidzunas [48], and Blair-Loy and Wharton [30].

[6] Following common usage at the university level in the United States, we use the term "department" to mean an academic unit devoted to one academic discipline, typically lead by a Chair. The terms "division" and "school", led by a Dean, are used synonymously as in "engineering school" to mean the set of engineering departments within a university.

Talks are generally advertised by posting flyers and by sending e-mail to faculty, postdocs, and graduate students in the academic department conducting the search for faculty candidates. The e-mail may get forwarded to people with related research interests in other departments, and it is common to have a few audience members from other departments. Faculty are the most active members of the audience and the ones most likely to ask the presenter questions.

We lack consistent data on the gender of audience members who ask questions. The presenter wears a microphone for clear audio and is consistently in the field of view of the camera. However, the audience members who ask questions may not be visible in the picture, and the audio sometimes leaves their gender unclear.

We constructed a sample of the archived videos in five engineering departments hosting job searches over two recent academic years.[7] For these departments, women applicants represent roughly 15% to 20% of all job applicants. Due to the small numbers of interviewees, the percentages of women in the interview pool varies from 0% to about 33% across different department job searches. Given the small proportion of women presenters in the population, we over-sampled women as follows. We used all the videos from women candidates, and attempted to match each woman with two men of the same seniority from the same department. Seniority is measured by the number of years post-Ph.D. Seniority ranges from 0 (people still finishing up their dissertations, called, colloquially, ABDs (All but Dissertation) or "baby Ph.D.s") to candidates with multiple years of experience post-Ph.D.

There were a few instances when the matching process was not exact. For example, three women ABD candidates were matched with five (rather than six) men ABDs, because there were not six men available in that seniority category in that department. In another example, a woman candidate seven years out after awarded a Ph.D. was matched with men who are seven and eight years out, because there were not two men available who were seven years out.

We refer to the faculty candidate as the "presenter", and the time they spend formally presenting their slides (excluding time responding to interruptions) as the "presentation". In our context of the job talk, we are concerned with the amount of time taken away from the candidate's nominal one hour of presentation time. Because we are interested in the presentation time and how interruptions and questions could affect the outcome of the talk or whether it is brought to conclusion, our analysis excludes the dedicated Question and Answer (Q & A) segment after the presenter has formally concluded the talk.

To code our data, we watched the videos with a playback that shows minute and second.

When an audience member asked a question, the coder paused the video and noted minute and second for the question start time, as well as end time. Likewise, the start and end times for answers were noted. The coding process involves a judgment call by the coder to decide what constitutes the end of an answer, when the presenter returns to the presentation.

3.2. Defining Types of Interruptions, Our Dependent Variables

In some previous studies, conversational interruptions have been defined in terms of syllabic measurements, for example as simultaneous talk which begins more than two syllables from the end of a current speaker's sentence [49] or in terms of grammatical, turn-construction units that are "hearably complete" [50]. Interruptions have also been defined in more contextual ways, for example taking into account whether a speaker has already made a point, or whether they are repairing a previous violation of their speaking turn [51,52].

Since much past research has focused primarily on interruptions in turn-taking conversation, it has required definitions of interruptions appropriate to that context. By comparison, there have been few studies of interruptions in scenarios with an audience and a presenter. Furthermore, in these latter studies, for example a psychology experiment involving hecklers during a speech [53]

[7] We did not include the total population of archived videos, due to the time and expense involved in the coding of each video.

or an examination of television coverage of a political speech [54], determining the existence of an interruption was straightforward and not a focus of the study.

Within the pre-Q & A period under analysis, we are concerned with any time that an audience member speaks, regardless of syntactic positioning. We define three types of speaking by audience members:

An *acknowledged question* is one where the audience member raises his or her hand, and is acknowledged by the presenter. This definition relies on the audience member's hand gesture and presenter's acknowledgement.

A *follow-up question* corresponds to a situation where the presenter has just finished answering a question from the audience, and a member of the audience asks another (follow-up) question. In this case, the audience member does not raise his or her hand but would not generally be expected to do so.

An *unacknowledged interruption* happens in one of two ways:

(1) If the presenter is presenting (rather than answering a question), then we expect an audience member to raise a hand, and so an unacknowledged interruption is defined by the audience member speaking without first raising his or her hand, even if the presenter has completed a sentence or a section of the talk. Thus, this definition relies on the lack of audience member hand gesture and presenter acknowledgement.
(2) If the presenter is answering a question, then an unacknowledged interruption is defined by an audience member speaking before the presenter has finished their answer. (In a few rare cases, an interruption arises from an audience member having a speaking overlap with another audience member). Our distinction between this case and the earlier definition of a follow-up question depends upon the contextual information about the presenter's completion of an answer.

The motivation for these definitions is as follows. When the presenter is presenting, there is a presumption that an audience member should ask permission to speak, so politeness is defined by raising a hand. In that phase, an audience member can speak either by asking permission (raising their hand and *getting acknowledged*, which is considered polite) or by *interrupting* (starting to speak without raising their hand, which is considered impolite whether or not the presenter has just finished a sentence, or a section of the talk). This speaking without raising one's hand is our first type of interrupting.

However, once the presenter has begun answering a question, the situation may be considered to have shifted into one more like conversational turn-taking, in which conversational politeness or lack thereof is defined by allowing the current speaker to complete their thought. Thus, in this phase, an audience member can speak either by waiting for the other person (presenter or other audience questioner) to finish his or her thought, in which case it is a *follow-up question* (which may be seen as questioning the presenter's authority but is not conversationally impolite) or *by interrupting* (not letting the presenter finish their answer, which is considered impolite). This speaking with speech overlap while the presenter is giving an answer is our second type of interrupting. Once the presenter returns to presenting, the situation returns to one in which the audience member should raise their hand to get permission to speak. We combine the two types of interrupting into one category, since they both indicate lack of politeness.

3.3. Meanings of Zero Questions

Based on our own experience in similar departments, and in conversation with other engineering faculty, we are aware of three meanings of "zero questions".

(1) The talk is very clear, so no questions are needed.
(2) The talk is way below the bar, so nobody bothers asking questions.
(3) The departmental culture does not involve asking questions before the formal Q & A period.

We cannot adjudicate between meanings 1 and 2. It is likely that meaning 3, the departmental culture explanation, does not apply to the five departments in our study. In each department, in most of the talks (91% overall), candidates received questions during the Pre-Q & A period.[8]

Table 1 provides an example of the collected data. Presentation time begins at 1 min 22 s; the time prior to that is the introduction. This composite example illustrates the situations that the coder must recognize: presenting yielding to an acknowledged question at 11:26 (hand gesture, acknowledgement), a presenter transitioning from answering a question back into presenting at 11:47 (context), presenter getting interrupted at 15:40 (no acknowledgement), a follow-up question at 15:51 (context), and an answer getting interrupted at 16:09 (context).

Table 1. Example of Raw Data.

Female, Ph.D. + 4 YEARS	Start	End	Duration
Presenting	0:01:22	0:11:25	10:03
Acknowledged Question	0:11:26	0:11:33	00:07
Answer	0:11:34	0:11:46	00:12
Presenting	0:11:47	0:15:40	03:53
Unacknowledged Interruption	0:15:40	0:15:44	00:04
Answer	0:15:45	0:15:51	00:06
Follow-up Question	0:15:51	0:15:54	00:03
Answer	0:15:55	0:16:09	00:14
Unacknowledged Interruption	0:16:09	0:16:11	00:02
Answer	0:16:12	0:16:18	00:06
Presenting	0:16:19	0:19:02	02:43

Our dependent variables also include the total number of questions, which is the sum of acknowledged questions, unacknowledged interruptions, and follow-up questions during one presenter's seminar. We also measure the audience time as the proportion of the pre-Q & A talk time taken up by audience members' questions (audience time/total pre-Q & A time). As noted above, all of these dependent variables are indicators of interruptions in a broader sense, because all of them occur before the final segment of the seminar, officially designated as the Q & A period.

4. Descriptive Results

Table 2 presents descriptive statistics for the dependent variables, broken down by gender. The left column shows the average values for men (standard deviations in parentheses below), while the middle column shows the average values for women. The right column shows the differences between the two groups (with standard errors in parentheses below).

Table 2 shows that women, on average, are asked about 1.8 more follow-up questions and about three more total questions than men. Women are asked about 12% more total questions than men. Running a *t*-test on the difference in average number of questions between men and women will be unlikely to return valid inference in this case because the dependent variable is either a count (number of questions) or a ratio (fraction of the talk). After presenting descriptive statistics on the explanatory variables, we will address the choice of appropriate models for these analyses.

8 In contrast, one department we had originally considered—Biomedical Engineering—had zero questions during the pre Q & A period in 81% of the talks, indicating a departmental culture of few to no questions. Our research questions entail understanding how gender may affect audience responses to the talk and affect the amount of time the presenter has to conclude the presentation. We therefore excluded the Biomedical Engineering Department from analysis.

Table 2. Descriptive Statistics: Dependent Variables.

Dependent Variables	Men	Women	Diff./(SE)
	Mean/(SD)	Mean/(SD)	
Unacknowledged interruptions	3.77 (4.87)	4.95 (6.21)	−1.18 (1.04)
Acknowledged questions	5.49 (4.89)	5.39 (4.07)	0.097 (0.89)
Follow-up questions	4.83 (4.76)	6.66 (7.02)	−1.83 (1.09)
Total questions	14.1 (11.6)	17 (13.9)	−2.91 (2.40)
Audience time proportion	0.038 (0.031)	0.050 (0.038)	−0.012 (0.0065)
N talks	78	41	

4.1. Explanatory Variables

Table 3 presents descriptive statistics for the explanatory variables, broken down by gender. Our focal predictor variable is gender. Our data set has different departmental indicators, including proportion of the faculty who are women and the specific departments (Computer Science, Electrical Engineering, and Mechanical Engineering) across two Universities. We also indicate experience post-Ph.D. Almost a third of the presenters are ABDs with an experience of 0 years. The highest end of the range is 21 years, with three observations over 12 years. To control skewing, we capped the high end at 12-plus years.[9]

Table 3. Descriptive Statistics: Explanatory Variables.

Explanatory Variables	Men	Women
Years since Ph.D. (mean/SD)	3.12 (3.84)	3.17 (4.35)
Proportion female faculty in department (mean/SD)	0.11 (0.06)	0.11 (0.06)
University		
University 1 (frequency, %)	60 (77%)	32 (78%)
University 2 (frequency, %)	18 (23%)	9 (22%)
Department		
CS (frequency, %)	43 (55%)	21 (51%)
EE (frequency, %)	32 (41%)	18 (44%)
ME (frequency, %)	3 (4%)	2 (5%)
N talks	78	41

4.2. Graphical Results

As a first step toward selecting an appropriate model, we show two overlapping conditional density histograms of the total number of questions, indicated in grey for men candidates and white for women candidates (Figure 1). This figure illustrates important patterns. One is the overwhelming number of questions—20 to 50—some candidates are faced with. Note that women experience more questions on average (see the vertical dashed line for the male average and the solid line for the female

9 Capping or not capping the experience variable at 12 years did not affect the substance or statistical significance of results.

average). There are few talks with zero questions (11), and women are more likely to experience zero-question talks.

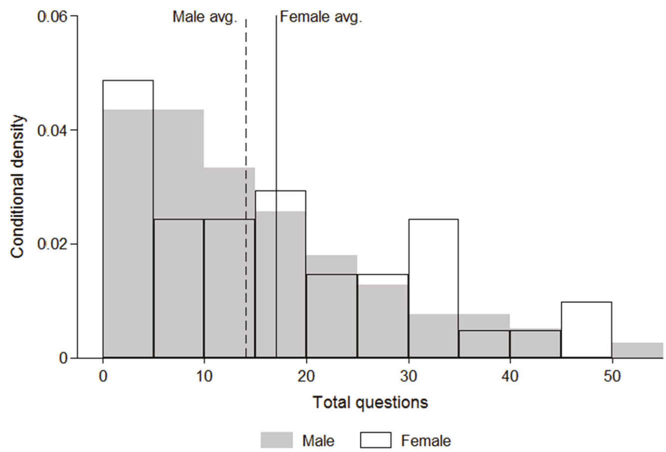

Figure 1. Total Number of Questions by Gender.

Next, Figure 2 presents a similar conditional histogram (grey for men, white for women), but the horizontal axis is the number of *follow-up* questions. Similar to the last figure, Figure 2 shows that women have a higher average number of follow-ups than men (see vertical dashed line for male average and solid line for female average). Moreover, most of the talks with a large number (12—30) of follow-ups, on the right hand side of the graph, have women presenters, indicated by the clear bars.

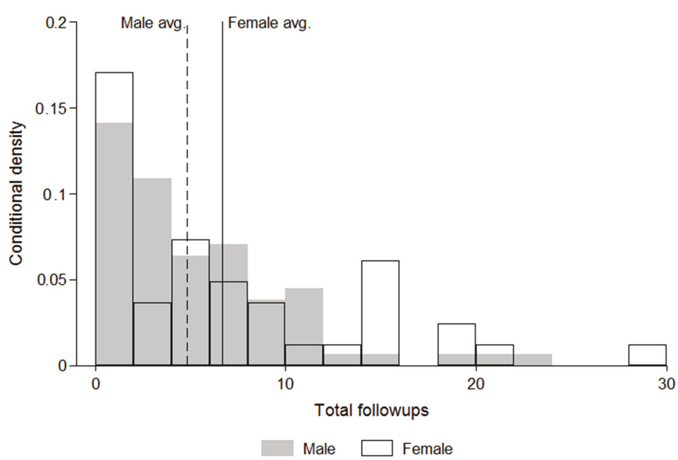

Figure 2. Number of Follow-ups by Gender.

These descriptive results provide preliminary answers to Research Question 1a: Women candidates receive more total questions and, among those, more follow-up questions, than men candidates.

5. Multivariate Results

To more formally assess the results illustrated in the histograms, we need to choose which model to use. The dependent variables for this analysis are counts of the number of questions of different types received by each candidate. In addition to being integer-valued, Figures 1 and 2 show that these counts are non-negative and are not normally distributed. To accurately model these data, therefore, we choose to use a count data method. The standard choices for modeling count data are a Poisson model, negative binomial model, or a zero-inflated version of either of these models [55]. We prefer a zero-inflated, negative binomial (ZINB) model for this analysis for empirical and theoretical reasons. Table 2 shows that the variance of each dependent variable is high relative to the mean, indicating that the data are over-dispersed. This feature means that the negative binomial model is more suitable than a Poisson model. Theoretically, department norms about whether to ask questions during a job talk also mean that some talks are more likely to have zero questions, making a zero-inflated model more appropriate.[10]

The ZINB model simultaneously fits two models. One model estimates the probability of observing zero questions. Since there are two possible states—zero questions or positive questions—this model uses a logit regression. The other model estimates the number of questions, conditional on the candidate receiving at least one question. This model operates like a typical negative binomial regression. Together, these models account for both the excess number of zero observations and for the positive-value count data. In the results shown below, the model for zero-question observations is shown in the bottom panel of the table, and the model for positive values is shown in the top panel.

We now estimate ZINB models to address *our first research question:* do women get more questions than men during the job talk? Table 4 shows that the answer is yes, in part. We focus on the top panel of the table, the model for positive values. For each row, the table lists the coefficient from the ZINB model. Below that is the exponentiated coefficient, and below that is the standard error in parentheses.[11] Consistent with Figures 1 and 2, the top panel of Table 4 shows that women face more total questions and more follow-up questions than men. Specifically, the coefficient for female is statistically significant in the models predicting the number of follow-up questions (model 3) and the number of total questions (model 4), controlling for the percent of departmental faculty who are women.[12] However, there is no gender difference in the number of unacknowledged interruptions.

Taking the exponential of the coefficients, as shown below each ZINB coefficient in Table 4, is helpful for interpretation. The coefficients for the positive values have a similar interpretation to the percent change—they now represent the factor by which the number of questions goes up when that variable increases by one.[13] Since the female coefficient of the number of follow-up questions (model 3) is 0.35, then exp(0.35) = 1.4, indicating that women get about 1.4 times more follow-up questions than

[10] In addition to the reasons for selecting the ZINB model given above, a statistical model selection procedure can also guide model choice. The software program Stata has a user-written routine, *countfit*, which provides diagnostics on which models to use. The models fit the dependent variable to the exponential of the right-hand side variable, thus constraining the predictions to be positive. For the zero-inflated models, we also specify a separate model for zeros to try to explain why some observations are zero. The decision of whether to use a Poisson or negative binomial is based on the mean of the dependent variable relative to its variance, after taking into account control variables. The Poisson model assumes that the variance of the dependent variable is equal to the mean. Table 2 suggests that this is not true, so we should also expect to prefer a negative binomial model. We fit the model predictions to the actual data at different levels of the dependent variable (results available upon request). These diagnostics indicate that for zero questions, both the Poisson (PRM) and negative binomial (NBRM) models are highly inaccurate. Both of the zero-inflated models perform well at zero, by construction. For positive numbers of questions, the Poisson and zero-inflated negative binomial (ZINB) models are the most accurate. From the fitting model predictions test, ZINB model is preferred.

[11] Because of limited variation, including the control variable university in the Table 4 model leads to numerical convergence issues for the acknowledged and follow-up question models. Therefore we exclude university from the model for positive values. We exclude university for the same reason in Table 6, below.

[12] In separate models (not shown), we substituted percent departmental faculty who are women with dummy variables for department (with CS as the excluded reference department). The results were substantively the same, with the same pattern of statistical significant coefficients for women candidates receiving more follow up and more total questions. For numerical reasons, we have also chosen to exclude the university control variable from the model for positive values.

[13] In cases where the variable is binary, the exponentiated coefficient has an interpretation very similar to the predicted value; it gives the relative increase or decrease in the dependent variable that results from being part of the group indicated by the dummy variable (female).

men.[14] Similarly, since the female coefficient for total questions (model 4) is 0.22, then exp(0.22) = 1.2, indicating that women get about 1.2 *times* more total questions than men, on average, conditional on getting more than zero questions. The exponential of the intercept shows that, conditional on being asked at least one question, the average male candidate would receive about 30 total questions from a hypothetical department composed of only male faculty. Thus, under this condition, *women get about* $1.2 \times 30 = 36$*, or six more total questions than men do, on average.*

Table 4 also answers *Research Question 2. Departments with a larger proportion of the faculty who are women pose fewer interruptions*, acknowledged questions, follow-up questions, and, of course, total questions than departments with a smaller share of women faculty.

Table 4. ZINB Models Predicting Questions (all dependent variables).

Model Number	(1)	(2)	(3)	(4)
	Num. Interruptions	**Num. Acknowledged**	**Num. Follow-Ups**	**Total Questions**
Model for positive values				
Female	0.26 1.3 (0.27)	−0.011 0.99 (0.14)	0.35 ** 1.4 (0.16)	0.22 * 1.2 (0.13)
Proportion female faculty	−8.83 *** 0.0001 (2.61)	−2.59 * 0.08 (1.39)	−7.44 *** 0.0006 (1.54)	−7.19 *** 0.001 (1.20)
Constant	2.32 *** 10.2 (0.22)	2.07 *** 7.9 (0.19)	2.36 *** 10.6 (0.17)	3.41 *** 30.3 (0.14)
Model for zeros				
Female	−0.52 0.59 (1.10)	0.18 1.2 (0.83)	1.84 * 6.3 (1.07)	0.75 2.1 (0.78)
Pct. female faculty	56.3 *** 2.8×10^{24} (20.7)	−34.7 *** 0.00 (11.7)	28.8 3.2×10^{12} (106.5)	−30.4 *** 0.00 (11.3)
University 1	2.24 9.4 (1.79)	−6.89 *** 0.001 (1.10)	−18.7 *** 0.00 (3.13)	−6.70 *** 0.001 (1.12)
Constant	−10.6 *** 0.00 (4.08)	5.52 ** 249.6 (2.22)	−5.94 0.003 (19.1)	4.47 ** 87.4 (2.08)
ln(alpha)	−0.22 (0.23)	−1.11 *** (0.21)	−0.70 *** (0.21)	−0.98 *** (0.18)
N talks	119	119	119	119

Notes: Columns 1 through 4 show the coefficients from zero-inflated negative binomial models. Significance is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are shown in parentheses. Below each coefficient (above the standard error) is the exponentiated value of that estimate, which can be interpreted as the factor by which the expected number of questions increases due to a one unit change in the independent variable for the top panel and the factor by which the odds of having no questions changes in the bottom panel. Robust standard errors are shown in parentheses.

[14] The interpretation of the coefficients for the positive values is similar to a log-linear model, so all coefficient values can also be read as approximate percent changes. This approximation is accurate for values less than about 0.1. For exact percent changes, take the coefficient, exponentiate, and subtract 1.

We now address *Research Question 1b*, whether women candidates, compared to men, generally find that a higher share of the total talk time is spent on audience time. Similar to count data, ratios are best handled by a specialized nonlinear estimation strategy. The standard practice is to use a binomial family estimator with a logit or probit link [56]. Table 5 presents results of a binomial estimator and logit link.[15]

Table 5. Binomial Model Predicting Audience Time.

Variables Predicting Audience Time	Binomial
	Audience time
Female	0.26 * (0.15)
Proportion female faculty	−5.74 *** (1.24)
Constant	−2.63 *** (0.15)
N talks	119

Notes: Binomial models use a logit link. Significance indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are shown in parentheses.

The binomial model in Table 5 performs similarly to an OLS model (results not shown). The binomial model should be interpreted as percent changes. It indicates that for female candidates, 1.3 times as much time is taken up by questions. From the summary statistics in Table 2, one can see that the audience takes up 4.3% of the total talk time, on average. The results from the model indicate, therefore, that roughly 5% of an average talk by a female candidate is taken up by the audience while 3.8% of an average talk by a male candidate is audience time.

We now turn to *Research Question 3:* Do junior candidates experience more questions than senior candidates? The ZINB models in Table 6 examine whether the presenter's professional experience mitigates interruptions. Here, we focus on the number of follow-up questions as the dependent variable.

Model 2 shows that there is a modest, yet statistically significant, decline in the number of follow up questions candidates receive if they have more experience. However, women still face more follow-up questions than men after controlling for years since Ph.D. In Model 3, the interaction term of woman candidate times experience is not statistically significant. In other words, having more experience does not differentially help women candidates. Men and women with more experience receive fewer questions than men and women with less experience, respectively, and this negative effect of years since Ph.D. on number of follow-up questions is the same for men and women.

The data presented so far do not indicate whether having more questions helps or hurts a candidate. We do not have measures of job offers. However, while coding the video recordings, we did monitor in qualitative language when candidates' verbal cues clearly indicate that they are rushing to get through their carefully prepared slide decks and reach the punch line of their talk. Example statements that indicate rushing include "For the sake of time, I'm going to skip this part", "There's not much time left; I will rush through this", "I'm going to skip to the end", "I'm going really quick here because I want to get to the second part of the talk" and "We're running out of time so I'm not going into the details". We find that rushing, as indicated by these cues, is correlated with the number of total questions (Pearson correlation coefficient 0.22) and with the number of follow-ups (Pearson coefficient 0.19). This suggests that having many questions may prevent a candidate from delivering

[15] We found virtually identical results for the effect of female when department dummies (with CS as the excluded reference category) were substituted for percent of the faculty who are women. Results not shown.

all their prepared content and may rush them in covering the key sections that are often placed at the end (summary of results, impact of results, future work).

Table 6. ZINB Models Using Gender and Experience to Predict Number of Follow-up Questions.

Model Number	(1)	(2)	(3)
	Num. Follow-Ups	**Num. Follow-Ups**	**Num. Follow-Ups**
Model for positive values			
Female	0.35 ** 1.42 (0.16)	0.35 ** 1.42 (0.16)	0.45 ** 1.57 (0.18)
Proportion female faculty	−7.44 *** 0.001 (1.54)	−7.70 *** 0.0005 (1.49)	−7.38 *** 0.001 (1.55)
Years since Ph.D.		−0.041 * 0.96 (0.024)	
Years since Ph.D. × female			−0.036 0.96 (0.040)
Constant	2.36 *** 10.59 (0.17)	2.50 *** 12.18 (0.16)	2.35 *** 10.49 (0.17)
Model for zeros			
Female	1.84 * 6.30 (1.07)	1.85 * 6.36 (1.07)	1.84 * 6.30 (1.07)
Proportion female faculty	28.8 3.2×10^{12} (106.5)	30.0 1.1×10^{13} (106.6)	30.6 1.95×10^{13} (106.6)
University 1	−18.7 *** 7.6×10^{-9} (3.13)	−18.4 *** 1.02×10^{-8} (3.87)	−18.6 *** 8.4×10^{-9} (3.82)
Constant	−5.94 0.003 (19.1)	−6.17 0.002 (19.1)	−6.27 0.002 (19.2)
ln(alpha)	−0.70 *** (0.21)	−0.74 *** (0.21)	−0.71 *** (0.22)
N talks	119	119	119

Notes: Columns 1 through 3 show the coefficients from zero-inflated negative binomial models. Significance is indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Below each coefficient, above each standard error, is the exponentiated value of that estimate, which can be interpreted as the factor by which the expected number of questions increases due to a one unit change in the independent variable for the top panel and the factor by which the odds of having no questions changes in the bottom panel. Robust standard errors are shown in parentheses.

6. Discussion

Our analyses shed light on a key set of interactional processes linked to the persistent under-representation of women faculty in academic engineering departments. Women academics who have made it to the short list in competitive academic job searches in top departments face more follow-up questions and more total questions during their job talks than men do, on average, even after controlling for years of experience post-Ph.D. Under the condition of at least one question being asked during the talk, women receive six more questions than men do, on average. Further, a higher proportion of women's talk time is spent on audience members' speech. This means that, generally, women have less time to present their prepared talk and slides.

The larger number of questions women receive on average is mostly driven by the larger number of follow-up questions. These are questions piled on to previous questions and thus may indicate a challenge to the presenter's competence—not only in their prepared talk but also in their response to questions. Consistent with research on greater scrutiny and stricter standards for higher prizes in masculine-typed occupations and "prove it again" bias, we find a Catch 22 for women. Even short-listed women with impressive CVs may still be assumed to be less competent, are challenged, sometimes excessively, and therefore have less time to present a coherent and compelling talk.

We have revealed subtle conversational patterns of which most engineering faculty are likely unaware. It is a form of almost invisible bias, which allows a climate of challenging women's competence to persist. These patterns may be linked to the small numbers of women faculty hired into these departments. Indeed, departments with a larger share of women faculty tend to ask fewer questions of all candidates (women and men), take up less of their time in audience speech, and thereby give candidates more time to complete their presentations.

6.1. Policy Recommendations

Our data set shows that a few candidates, both women and men, receive a very large number of questions, in the range of 30 to 50. In some cases, a presenter rushes through slides at the end, or decides to skip a large number of slides. In other cases, the talk runs over by 15–20 min, and the audience dwindles. It may be advisable for each talk to have a facilitator, perhaps a senior faculty member who introduces the presenter, who will pay attention to the number and also the tone of questions being asked. If the number of questions becomes large and especially if the tone seems hostile or the presenter seems to be rushing, the facilitator could ask the audience to hold their remaining questions for the Q & A session at the end. Sometimes presenters may make this request themselves, but it may be difficult for a young ABD candidate to make this request to an audience of senior faculty. If there is no assigned facilitator, it may be appropriate for a senior faculty member in the audience to make this request.

When the suggestion of having a facilitator stop questions was made in one department, a faculty member protested that if he did not ask his questions as the talk went along, he would not understand the subsequent material, and the remainder of the talk would be useless. While this is a legitimate argument, his preference to ask multiple questions should be balanced against the preferences of others in the audience who may be fully understanding the talk and would be better served by having the presenter complete the material.

It would also be helpful for young faculty applicants to be aware that there are large differences in university or departmental culture, so that they are prepared for this. For the five engineering departments in this study, only 9% of talks had zero questions. In contrast, the Biomedical Engineering Department that was excluded from the study, 81% of talks had zero questions. Especially candidates in interdisciplinary sub-fields may be surprised if they have a mixed audience with differing cultures in this regard. Applicants should also know that some talks get derailed by questions, and it is an acceptable option for the presenter to ask the audience to hold remaining questions for the Q & A session at the end. We encourage advisors and mentors to share this knowledge with their graduate students and postdoctoral fellows.

6.2. Limitations

Case studies are, by design, not necessarily representative of other organizations. Our analysis of job talk video recordings is pioneering. However, the data have a number of limitations. We were limited to the departments which had archival video recordings. We constructed a theoretical framework from well-established literature on the unequal treatment by *gender* in terms of competence and hirability evaluations and the likelihood of being interrupted. Future research should adapt these insights to the study of the effects of candidate race. Moreover, the nature of our access to the archival video recordings precluded us from measuring which candidates were later voted by departmental faculty as worthy of receiving job offers. Note that even if it had been possible for us to investigate job offers in our data, defining this outcome would be problematic. Some top candidates may not receive a formal offer if they have already received—and potentially accepted—offers from other departments further ahead in their recruitment process. We encourage future researchers to investigate these issues in other research-oriented STEM departments.

7. Conclusions

This study analyzed video recordings of job talks in five engineering departments. We found that, compared to men, women with similar years of experience receive more follow-up questions and more total questions and spend less time on their prepared talk. These subtle differences in how women and men candidates are treated persist, likely outside the conscious awareness of hiring departments. More broadly, we assess how gender barriers emerge within the context of actual work units and vary depending on social structural features of the work units. For example, we found that there are more audience interruptions in departments with a smaller proportion of women. We urge future researchers to examine the connections between the number of questions posed at the job talk and actual job offers extended to candidates. Since these patterns operate under the radar, they are not seen to contradict the broader cultural belief that academic science is a meritocracy, in which the best scientific ideas are objectively assessed and rewarded [57,58].

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social sciences

Article

Gendered Perceptions of Cultural and Skill Alignment in Technology Companies

Alison T. Wynn * and Shelley J. Correll

Department of Sociology, Stanford University, 450 Serra Mall, Stanford, CA 94305, USA; scorrell@stanford.edu
* Correspondence: atp5@stanford.edu; Tel.: +1-650-723-3956

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Abstract: Previous research documents how stereotypes discourage young women from choosing and attaining technology jobs. We build off this research and ask whether (and how) stereotypes continue to affect men and women once they enter the technology workforce. Using a novel survey of technical employees from seven Silicon Valley firms and new measures of what we call "cultural" and "skill" alignment, we show that men are more likely than women to believe they possess the stereotypical traits and skills of a successful tech employee. We find that cultural alignment is especially important: because women are less likely than men to believe they match the cultural image of successful tech workers, they are less likely to identify with the tech profession, less likely to report positive supervisor treatment, and more likely to consider switching career fields. This paper is the first to use unique and independent measures of cultural and skill alignment comparing employees' perceptions of themselves to their perceptions of an ideal successful worker. By allowing cultural and skill alignment to operate separately, we are able to determine which work outcomes are most strongly related to each form of alignment. Our results imply that if we can broaden the cultural image of a successful tech worker, women may be more likely to feel like they belong in technology environments, ultimately increasing their retention in tech jobs.

Keywords: gender; technology; work and occupations; stereotypes

1. Introduction

> "When most people think of the average tech entrepreneur, the pale guy who codes while playing World of Warcraft in his gadget-filled basement pops up." (Wei 2012).

This quote comes from a *Washington Post* article written by a woman venture capitalist in Silicon Valley describing the masculinized culture of technology. According to the article, women do not relate to this image of a tech worker as readily as men do, and thus women may be less likely to believe they belong in tech jobs. This weak sense of alignment could cause a variety of negative work outcomes for women.

Existing literature and policy to increase the number of women in tech jobs are primarily concerned that young women lack the skills, or at least the confidence in their skills, to enter and succeed in tech jobs. However, as we show below, these skill-based perceptions often matter less than cultural perceptions. Cultural images (like the guy in his gadget-filled basement) can make women feel like they do not match the stereotypical portrait of a successful tech worker. In this paper, we examine the way stereotypic images of tech workers influence the career progression of men and women technical workers.

According to a recent report written by the US Department of Commerce (Beede et al. 2011), women currently make up about half of the US workforce; yet, they hold only 24% of jobs in science, technology, engineering, and math (STEM) fields. The report further notes that even as women's share of the college-educated workforce has increased over the past decade, women's underrepresentation in STEM fields has remained relatively constant. Furthermore, while 40% of men with STEM college degrees work in STEM jobs, only 26% of women with STEM degrees do. Women also leave STEM jobs at higher rates than women leave other professional jobs, particularly early in their careers (Glass et al. 2013). These gender disparities have important implications for lifetime earnings; women in STEM jobs earn 20% more than comparable women in non-STEM jobs (Beede et al. 2011).

Gendered stereotypes about math and science can impede the entry and retention of women in STEM fields. Stereotypes are widely shared cultural beliefs about categories of people. In the case of STEM domains, stereotypes include beliefs that men have more ability than women do (Davies et al. 2002; Nosek et al. 2002; Spencer et al. 1999). As we describe below, research has established that negative stereotypes about young women's math ability can affect their mathematical performance, self-assessments of their competence, interest, confidence, and sense of belonging in STEM activities (Steele 1997; Correll 2001; Murphy et al. 2007; Cech et al. 2011; Cheryan et al. 2009). Ultimately, stereotypes can shape the choices and aspirations of men and women considering STEM fields (Cech et al. 2011). In addition, stereotypes also cause women to be judged by a harsher standard than men and to have their achievements devalued or ignored in STEM fields (Foschi 2000; Moss-Racusin et al. 2012).

To combat the effects of stereotyping, policy makers have suggested many different interventions to enhance the pipeline of women entering STEM fields: reshaping high school and college programs, enhancing mentorship of young women, fostering interest at a young age, increasing visibility of female role models, and actively recruiting women (Hill et al. 2010; Huhman 2012; Margolis and Fisher 2002). These interventions aim to increase girls' entrance and participation in math and science. However, few policies actively engage women once they have entered STEM careers (The NSF ADVANCE program is a notable exception; see www.nsf.gov/advance).

Underlying current pipeline policies is the assumption that if we can help young women in their more formative years continue on the path toward careers in STEM fields, the negative effects of stereotypes will disappear or be less relevant once these women enter the workforce. On the one hand, this assumption makes sense and is largely consistent with current understandings of why stereotypes have the effects that they do. Empirical studies have supported theoretical predictions that stereotypes impact judgments most heavily when there is some uncertainty about how to assess ability (Correll 2004; Reskin and McBrier 2000; Uhlmann and Cohen 2005). If women persist long enough in STEM careers, they may garner considerable evidence of their skill and ability; this successful history may reduce uncertainty about whether they possess the skill necessary to achieve continued success in a STEM field. It seems logical to predict, then, that with this reduced uncertainty, negative stereotypes may cease to influence their self-assessments and choices over time.

On the other hand, perhaps stereotypes continue to influence people's decisions and perceptions once they are in the workplace. In any workplace, new tasks and roles emerge all the time, and employees must continuously adapt to new situations. These changing elements can create uncertainty, and negative stereotypes may resurface, reigniting women's doubts about their ability and sense of belonging. This would lead to the alternative prediction that the same stereotypes that decrease middle school, high school, or undergraduate women's interest in STEM fields may continue to affect women once they are on the job.

Using a unique dataset of men and women technical employees in Silicon Valley firms, we ask whether stereotypes continue to affect the judgments, decisions, and perceived treatment of women and men once they have made it through the educational pipeline and are working in a STEM job. To our knowledge, this is the only survey of its kind conducted with actual tech workers. While previous literature has documented the attrition of women out of science and engineering, and scholars are quite concerned about the dearth of women in these fields, this is one of the first papers to examine the effect of stereotypes on women who are working in tech jobs. Furthermore, while some emerging qualitative research examines women in Silicon Valley tech firms (e.g., Alfrey and Twine 2016), this is the first survey analysis of both men and women currently working in such firms. In particular, we examine whether women are less likely than their male counterparts to perceive that they align with stereotypes about successful tech workers.

We create novel measures that we call "cultural alignment" and "skill alignment."[1] We define cultural alignment as the extent to which a tech employee believes she or he matches the attributes of a stereotypical successful tech worker. Widely shared images of successful tech workers—such as the coding-obsessed geek—can create a sense of belonging in those who believe they match the image, and a sense of alienation in those who do not. We define skill alignment as the extent to which a tech employee believes he or she possesses the skills of a typical successful tech worker. Tech companies expect their employees to demonstrate a range of quantitative and analytical skills, and employees may or may not believe they match the desired skill profile. In addition, we explore how these feelings of alignment (or lack of alignment) are related to career outcomes. If women are less likely than men to believe they match the cultural image or skill profile of a successful tech employee, how does this belief influence their intentions to stay in technology and their perceptions of how they are treated by their supervisors? How do perceptions of alignment, fueled by stereotypes, influence work outcomes for men and women who are already in tech careers?

This paper offers a number of important theoretical contributions. First, this paper clarifies the distinction between cultural and skill-based forms of alignment with the prevailing standard in one's work context. While other authors have explored similar dimensions (Cech et al. 2011), this is the first paper to operationalize the distinction between culture and skill by comparing individuals' beliefs about themselves to their beliefs about successful workers in their field. By allowing these dimensions to operate separately and exploring the variance each explains in important gendered outcomes, we offer novel insight into the mechanisms that perpetuate gender inequality even once women have entered STEM fields. The masculine culture of technology has been cited as a key deterrent for women, but it is currently difficult to disentangle the effects of skill-based alignment from the culture of these settings. Second, this paper offers insight into the kinds of outcomes related to cultural and skill alignment. While skill alignment may be more important for certain outcomes, cultural alignment may be more significant for others. For example, is cultural alignment more strongly associated with women's identification with the tech field and their companies, as compared to skill alignment? What about supervisor treatment? It is possible women perceive a lack of sufficient skill, thereby identifying less with their professions and anticipating worse treatment by their supervisors, but it is also possible that cultural alignment is more strongly associated with these outcomes. We currently lack research adjudicating between these competing arguments. This distinction has important practical implications since it can help guide policy interventions toward the right problems, thereby increasing the number of women in tech fields.

Before turning to the data that allow us to answer these questions, we first briefly review what is known about how stereotypes contribute to men and women's uneven movement into STEM fields.

2. How Stereotypes Affect Perceptions in Tech Fields

Decades worth of research by sociologists and psychologists show that widely held beliefs about groups of people, as encoded in stereotypes, function as cognitive shortcuts in decision-making (Correll et al. 2017; Podolny 2005; Tiedens and Linton 2001; Weary et al. 2001). That is, under conditions of uncertainty about how to make judgments, stereotypes influence evaluations of self and other. Below, we review how gender stereotypes affect self-perceptions of skill, self-perceptions of fit or belonging, and perceptions of treatment by others, and we draw out the implications of this research for understanding the way stereotypes might impact women who are in technical jobs.

[1] Our measures complement, but are distinct from, measures used by others, such as Cech and coworkers' measure of "professional role confidence" (Cech et al. 2011) and Rivera's measure of "fit" (Rivera 2012).

2.1. Self-Perceptions of Skill

Stereotypes can powerfully affect how women see themselves progressing in math-intensive subjects and technical careers. Particularly among people who highly identify with a domain (for example, high-achieving women in tech fields), stereotype threat can significantly undermine performance (Beilock and Carr 2005; Steele 1997; Shih et al. 1999). Low performance can subsequently reduce identification with the relevant domain (Steele 1997).

In addition to impairing performance, stereotypes can influence self-assessments of ability and aspirations for future opportunities. In the case of mathematics, even when male and female high school students receive equal objective scores on tests of mathematical ability, young men tend to rate themselves higher in mathematical ability than young women do (Correll 2001). Similarly, Cech and colleagues found that male college students rate their engineering ability higher than women do, even though men and women have similar college grade-point averages and SAT scores (Cech et al. 2011). These higher ratings by men do not occur in domains that are not stereotyped as masculine (Correll 2001; Correll 2004). As Correll (2004) demonstrates, when negative stereotypes are salient, women judge their own performance by a harsher standard than men do, requiring more evidence of their skill before believing they have sufficient ability to succeed in a male-typed field (see also Cheryan et al. 2011). Furthermore, these self-assessments can shape future career aspirations and decisions (Correll 2001; Correll 2004). In this way, the gender gap in mathematical self-assessments contributes to the underrepresentation of women in STEM college majors.

If we apply this literature to the case of women who are already in technical jobs, we might expect that they, like younger women, would continue to judge their own performance by a harsher standard and, if so, they would be less likely to see themselves as possessing the skills of a typical successful tech worker. In other words, their skill alignment would be lower than that of their male counterparts. Since gender self-assessments have been shown to affect career decisions (Correll 2001; Correll 2004), we predict that lower skill alignment will be negatively associated with important career outcomes. However, the alternative prediction is that since women technical workers have already earned technical degrees and entered technical jobs, they have garnered considerable evidence of their technical skills, thereby reducing their uncertainty about their own abilities. If so, we might expect that the gender gap in skill alignment would be small or even non-existent.

2.2. Self-Perceptions of Belonging

In addition to affecting performance and self-assessments of ability, stereotypes can also decrease women's interest in pursuing STEM majors and careers by making women feel like they do not fit or belong in these fields. In an experiment by Davies and colleagues, viewing gender-stereotypic television commercials led women to avoid math questions in favor of verbal questions and indicate less interest in quantitative educational and vocational domains (Davies et al. 2002). Similarly, Murphy and colleagues conducted an experiment where undergraduates who were "highly math-identified" and who were majoring in a STEM field watched a video promoting an upcoming conference (Murphy et al. 2007). Women who watched a video with an unbalanced ratio of men to women displayed more signs of anxiety and fear of negative treatment, and reported less desire to participate in the conference, compared with women who watched a gender-balanced video. Whether the video was balanced or unbalanced had almost no effect on men. Importantly, this study demonstrates how features of a setting can make masculine stereotypes salient, thereby creating a threatening environment where women are less likely to feel like they belong. Subtle situational cues can trigger both objective (cognitive and physiological vigilance) and subjective (decreased sense of belonging and fit) experiences of threat. Threatening features of a setting can cause even highly confident, domain-identified women to lose interest in STEM activities and fields.

Cheryan and colleagues similarly show how physical environmental cues and interactions can influence women's sense of belonging and subsequent interest in computer science (Cheryan et al. 2009; Cheryan et al. 2011). In one experiment, changing the objects in a computer science classroom from masculine objects (such as geeky posters) to more neutral objects (such as nature scenes) significantly raised women's interest and sense of belonging (Cheryan et al. 2009). Stereotypical images can reinforce women's feeling of alienation in masculine fields and decrease their interest in pursuing future opportunities.

To the extent that stereotypes make women feel like they do not fit or belong in STEM majors or careers, we would expect that women will be less likely than their male counterparts to believe they match the cultural image of a successful tech worker. Furthermore, since technical workplaces are even more heavily male-dominated than STEM college majors (Beede et al. 2011) and often embody a masculine or "frat like" culture (Wynn and Correll 2014), we predict that women will have a lower level of cultural alignment than their male counterparts, even once on the job. Given the literature reviewed above, we predict that lower cultural alignment will lead women to feel like they do not belong in tech careers, thereby increasing the odds that they will leave these careers.

2.3. Perceptions of Others' Treatment

In addition to shaping women's self-perceptions and choices, stereotypes also affect the way women perceive others' judgments and behaviors. Women in STEM fields are often judged by a harsher standard than men by gatekeepers such as employers and teachers (Foschi 1996; Foschi 2000; Heilman 2001; Moss-Racusin et al. 2012). Heilman (2001) argues that stereotypical gendered expectations negate the recognition of women's accomplishments, either through the devaluing of their work or through attributing responsibility for their success to something other than their skill and ability. For example, a recent study found that science faculty rated a student applicant for a science lab manager position more highly when the application had a man's name than when the very same application had a woman's name (Moss-Racusin et al. 2012). Faculty considered the man more hirable and competent, and they offered him a higher starting salary and more career mentoring, than the identical woman applicant. Research on the effects of stereotypes in other male-typed domains finds similar effects to those found in the STEM fields (Steinpreis et al. 1999).

As these studies show, in domains that are either numerically or culturally associated with men, gatekeepers judge women's performance by a harsher standard. Therefore, we predict that, in addition to judging their *own* performances by a harsher standard, women tech workers will expect to face harsher judgments from their employers than men do. Perceptions of harsh treatment can have a profound effect on women's careers. Previous research has demonstrated that perceptions of career opportunity and discrimination affect self-esteem and confidence, health and wellbeing, job performance, job commitment, and aspirations for future career prospects (Ensher et al. 2001; Kaiser et al. 2004; Kanter 1977; Markham et al. 1985). When people feel they are being treated poorly or that they do not belong in a particular setting, they may disengage, becoming less involved in and committed to their work (Ensher et al. 2001; Gutek and Tsui 1996; Hausmann et al. 2009; Stainback and Irvin 2012). Ultimately, these choices and aspirations can affect employee performance and organizational rewards. If women are more likely than men to expect discrimination in technical careers, these expectations can cause unequal career setbacks and stymied advancement (compounding the effects of the discrimination itself).

2.4. The Current Research

While existing research demonstrates how stereotypes affect women's persistence in STEM fields at early life stages (e.g., high school and college), we continue to lack evidence about whether stereotypes continue to affect women once in a technical job. With what we believe is the only existing survey data from actual tech workers, we build on prior work by broadening our understanding of whether and how gender stereotypes matter in an important but understudied stage in the career life course of technical workers. We further explore how stereotypes about the culture of technology and the skills of technologists operate differently, and we analyze their independent effects on important gendered outcomes. We now turn to describing our data and our models for assessing the relationships between alignment and work outcomes for men and women in technical careers.

3. Data

Our data come from a dataset of men and women technical employees called "Climbing the Technical Ladder." In 2007, the Anita Borg Institute for Women and Technology and the Clayman Institute for Gender Research at Stanford University conducted a survey of technical men and women in the Silicon Valley (Simard et al. 2007). The San Francisco Bay Area's "Silicon Valley" is a region characterized by a high concentration of high-technology companies, providing a unique window into the technology world. Silicon Valley firms pride themselves on being meritocratic; organizational hierarchies are flat, and innovative start-up mentalities pervade. However, gender researchers suggest that widely shared gender beliefs are often carried into these new spaces (Ridgeway 2011), and technology companies often have a masculine or "fraternity-like" culture (e.g., Alfrey and Twine 2016; Wynn and Correll 2014). Using a sample of technical employees from seven Silicon Valley firms, we examine whether women perceive themselves as less aligned with the image of success than men; if so, we explore how this gender gap relates to employees' career decisions and opportunities.

Much in the same way that Cech and colleagues studied the experiences of men and women STEM students in four US universities to delve deep into a heretofore unstudied process (Cech et al. 2011), we draw on data from seven tech companies to examine cultural and skill alignment. This research setting is rare and particularly useful for empirically analyzing the impact of stereotypes on women currently working in STEM careers. The seven tech companies in our dataset include organizations within the broad computer and information technology industry as well as companies that employ top technical talent.[2] The primary industry segments represented are hardware and software. Surveyed employees comprised the core Silicon Valley technical workforce at each participating company. Thus, our sample contains data from employees actively working in technical jobs. The survey included questions about demographics, attitudes towards and perceptions of technical work, retention and advancement, and family. The survey was administered online to all employees in each company's core Silicon Valley technical workforce over a seven-month period in 2007–2008. The survey was administered to 12,805 employees across the seven participating companies. In total, 1795 employees completed the survey; thus, the overall response rate is 14%. Because the response rate is low, we should interpret the results with caution.[3] While a higher response rate is always desirable, having a sample of actual tech workers is unusual. With these data, we can provide novel insight into processes that affect women and men's experiences in tech fields.

The sample is similar to the broader Silicon Valley population in race and ethnicity, median income, and percent foreign-born (as well as country of origin). Women comprise 34.2% of the sample and 24% of the Silicon Valley engineering and computer population; thus, there is a slight overrepresentation

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2 Research directors at the Anita Borg and Clayman Institutes recruited seven companies to participate in the study. Their recruitment strategy was designed to capture organizational variation within the broad computer and information technology industry and to focus on companies that were known to employ top technical talent. We are unable to name the companies due to promised confidentiality. At the time the survey was completed, software and hardware industry segments were the largest employers in the high-technology sector in Silicon Valley, and these industry segments constitute the company sample. Surveys were administered to employees who comprised the core Silicon Valley technical workforce at each participating company; companies defined their "core technical workforce in the Silicon Valley region" for the researchers. The vast majority of survey respondents identified their field of expertise as software development/engineering and hardware engineering. For more information about the survey methodology, see (Simard et al. 2007).

3 Some recent research indicates that low response rates are not necessarily associated with significant declines in sample representativeness (Chang and Krosnick 2009; Curtin et al. 2000; Keeter et al. 2000). For example, Chang and Krosnick (2009) found that a sample with a 25% response rate was just as representative as a 43% response rate sample. In addition, response rates have generally declined over time, and the response rates obtained today are considerably lower than those obtainable in 1980, holding budget constant over time (Chang and Krosnick 2009; Holbrook et al. 2003).

of women.[4] The analyses presented below were conducted on cases for which there are no missing values on any variables included in the models (88% of the sample).[5] The final sample includes 1582 respondents: 1048 men and 534 women.

4. Analytical Plan and Measures

We first assess the cultural and skill-based stereotypes tech workers hold about successful technical work. We then assess the extent to which male and female tech workers align with these stereotypes and, if so, whether these differences in alignment contribute to gender gaps in work outcomes. After establishing the distinction between cultural alignment and skill alignment, we ask whether cultural or skill alignment has a larger impact.

4.1. Dependent Variables

Men and women's perceptions of how well they conform to cultural and skill expectations at work are related to a number of work outcomes. We include dependent variables capturing a range of work factors, described below, to determine the nature of resulting gender inequality. Answer choices on all dependent variable survey questions range from 1 (not at all descriptive/strongly disagree/definitely not) to 5 (extremely descriptive/strongly agree/definitely will).[6]

4.1.1. Identity Measures

The extent to which individuals identify with a field can influence their career-relevant judgments and decisions, thereby affecting what is commonly called the "pipeline" of women in STEM careers (Meyersson Milgrom and Petersen 2006). Our survey questions ask participants to rate the extent to which they personally *identify with the tech profession* and *identify with their companies.*

4.1.2. Supervisor Treatment Measures

Perceptions of the judgments and behaviors of gatekeepers such as teachers, supervisors, and employers can also affect men and women's career progress. Barriers or "glass ceilings" often prevent one group from achieving the same level of success as another group (Hymowitz and Schellhardt 1986). Our survey questions ask respondents about their supervisor's treatment: does their *supervisor value their opinions*, and does their *supervisor assign them high-visibility projects*? Being assigned to high visibility projects is crucial for promotion in tech companies (Correll and Mackenzie 2016; Silva et al. 2012).

It is important to note that our supervisor treatment variables represent respondents' *perceptions* about their supervisors' treatment. Though our data cannot reveal whether supervisors actually treat respondents as they reported, perceptions of supervisor treatment can have a profound effect on life outcomes, as described above. Therefore, if cultural or skill alignment contributes to the gender gap in perceptions of supervisor treatment, this finding would have important implications for workplace gender inequality more broadly.

[4] Because women are underrepresented in the larger tech industry, an overrepresentation in the sample facilitates analysis by gender. While some might claim sample overrepresentation requires weights, others have argued that sampling weights are not necessary in multivariate analysis if the weight is not a function of the dependent variable, and that weighting in multivariate analysis, at least with the OLS estimator, actually produces inefficient estimates (Winship and Radbill 1994). Thus, we did not include sampling weights in our analysis.

[5] We also ran our analyses with multiple imputation using a multivariate normal model (models available upon request). The patterns of results remain the same. Though some findings change slightly in magnitude and/or in level of significance, our overall arguments remain unchanged. Since very few data are missing, deleting the missing cases does not change our results substantially.

[6] For the "plan to switch career fields" variable described below, there is a "don't know" answer choice, which we coded as missing.

4.1.3. Turnover Intention Measure

To measure turnover intentions, the survey asks participants the extent to which they *plan to switch career fields* in the next 12 months.

4.2. Independent Variables

Tech employees in the sample were first asked to identify the attributes of people who succeed in technology. These questions allow us to assess what stereotypes they hold about successful tech workers. Later in the survey, respondents were asked to identify the attributes that describe themselves. To the extent that their stereotypes of successful tech work overlap with their descriptions of themselves, we define the employees as perceiving that they "align" with the prevailing stereotype of success.

4.2.1. Stereotypes about Successful Tech Work

Respondents were given a set of attributes (listed below) and asked, "In your opinion, to what extent are the following attributes TRUE of *people who succeed in technology*?" (Answer choices are on a 5-point scale ranging from "not at all true" to "extremely true"). Guided by a principle-component factor analysis, we determined that participants' beliefs about successful tech workers coalesced around two types of traits: cultural and skill-based. These categories emerged inductively from the data; in other words, the cultural traits and skills loaded onto separate factors during our analysis.[7] Thus, we created two variables: a scale of cultural traits of successful tech workers and a scale of the skill set of successful tech workers.

The *cultural traits scale* is the average response from questions about the extent to which each of the following traits described the successful tech worker: obsessive, assertive, cool, geeky, young, and long working hours ($\alpha = 0.66$).[8] Together, these traits constitute the stereotypical image of the "geeky coder," a young man who stays up all night obsessively coding. We ran models with several different specifications of the scale (e.g., we dropped one of the items from the scale such as "long hours"). The claims we make below are robust across models. Results are available upon request.

Because this coder image often pairs with concrete human capital skills, we created a separate *skill set scale* for the skills believed to be associated with successful tech work. After all, the stereotypical geeky coder is also a talented and proficient worker. The skill set scale is the average response from questions about the extent to which each of the following traits described the successful tech worker: analytical, questioning, and highly mathematical ($\alpha = 0.60$). These skills are often considered essential for success in the tech world. The Pearson's bivariate correlation between the cultural and skill scales describing successful tech workers is 0.243. Additional correlations between scale items are available in the Appendix A.

4.2.2. Self-Perception Scales

After rating successful tech workers on the attributes above, respondents were then given the same list of attributes and asked how much the attributes described *themselves*. We created a *cultural traits self-rating scale* ($\alpha = 0.56$) by averaging how participants rated themselves on the items loading on the cultural factor and a *skill set self-rating scale* ($\alpha = 0.61$) by averaging how participants rated

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7 We used principal-component factor analysis with varimax orthogonal rotations to derive the cultural and skill dimensions. The cultural dimension is a combination of two factors: intensive work commitment and geeky personality. We combined these factors due to their theoretical relevance to cultural perceptions of tech workers. The skill dimension is comprised of one factor. More information is available in the Appendix A.

8 The scale is constructed by dividing the sum of the question responses by the total number of questions answered. Thus, a value is created for every observation for which there is a response to at least one item (i.e., at least one variable in the scale is not missing). The summative score is divided by the number of items over which the sum is calculated. The scale value thus represents an average.

themselves on the items loading on the skill set factor.[9] The Pearson's bivariate correlation between the scales describing self is 0.344.

4.2.3. Cultural and Skill Alignment Measures

The variables above measure how individuals rate themselves and how they rate successful tech workers. To measure the extent to which individuals believe they match the cultural image or skill expectation of successful tech workers, however, we need to compare *each individual's* self-rating to how the same individual rates successful tech workers. If their image of self is similar to their image of a successful tech worker, we describe them as believing they "align." If women are less likely than men to believe they match the cultural image and skill expectations of successful tech workers, they may experience negative work outcomes. Below, we describe more fully how we created our alignment variables.

First, we created dummy variables that measure whether self-ratings of cultural traits and skill sets match the cultural and skill dimensions of successful tech workers. If the respondent sees himself or herself as equal to or greater than their own rating of the average successful tech worker, the *cultural alignment dummy* variable is coded as 1. This indicates that respondents see themselves in line with the cultural and personality traits of successful tech workers. If the respondent sees himself or herself as lower on the culture scale than their own rating of a successful tech worker, then the dummy variable equals 0, indicating a lack of alignment.

Similar to the cultural alignment dummy variable, the *skill alignment dummy* variable codes those who see themselves having equal or greater skills than the average tech worker as 1, and those who see themselves as less skilled as 0. Thus, these two dummy variables indicate whether respondents perceive themselves as successful on both cultural and skill dimensions. Importantly, these items do not ask individuals to directly compare themselves to a successful tech worker, but rather to assess the attributes of a successful tech worker and then, later in the survey, to assess themselves using the same list of attributes. In this way, our measures of alignment differ from related measures of "fit" or "professional role confidence" used by other researchers (Cech et al. 2011; Rivera 2012).

While these dummy variables provide useful information about cultural and skill alignment, we are also interested in the *magnitude* of any discrepancy between self-ratings and images of the successful tech worker. If women see themselves as less successful than men, does the *extent* of this difference matter?

Therefore, we created a second alignment variable that is the absolute value of the difference between a respondent's self-rating and his/her own rating of successful tech workers. The *cultural alignment absolute value* variable indicates how wide the gap is between self and successful tech worker on the cultural alignment scales, and the *skill alignment absolute value* variable indicates the gap on the skill-based scales.

For example, if an individual rates herself as a 2 on the cultural scale and 3 on the skill scale, and she rates a successful tech worker as a 5 on both the cultural and skill scales, she would be coded as a 0 on both the cultural and skill dummy variables because her self-rating is lower than her impression of a successful tech worker. Her value on the absolute value variables would be 3 for culture and 2 for skill, indicating that she considers herself further from the successful tech worker on the cultural dimension compared to the skill dimension.

To simultaneously consider both the direction and the magnitude of any gap, we will add an interaction between the absolute value and dummy variables to our regression models below. This analytical procedure, which we call a "direction-magnitude interaction model," is rather

[9] Because self-ratings are more complicated and nuanced than ratings of successful tech workers, they do not align as neatly with particular "types." Thus, we prioritized obtaining a good scale (i.e., higher Cronbach's alpha values) for the ratings of successful tech workers rather than self-ratings. Factor loadings and bivariate Pearson's correlations of the scale items are available in the Appendix A. Breakdowns by gender are available upon request.

untraditional, but as we describe below, it allows us to analyze both direction and magnitude of alignment independently.[10]

4.2.4. Gender and Race Measures

We also include variables tracking respondents' *gender* (Female and Male) and *race* (White, Asian, and Other). Gender is represented with a dummy variable where female is coded 1 and male 0. For Race, we introduce a dummy variable for Asian and Other, with White serving as the reference category. Unfortunately, we only have sufficient sample size to divide our sample into three racial categories. Consistent with the larger tech industry, our sample comprises mainly White (55%) and Asian (38%) respondents. Respondents were able to choose more than one racial category; thus, when coding the race variables, we included only respondents who exclusively chose "White/Caucasian" in the "White" category. We included in the "Asian" category anyone who chose "South Asian (Indian subcontinent/South Asian American)," "Southeast Asian/Southeast Asian American," "East Asian/East Asian American," or "Other Asian/Asian American." Our "Other Race" category includes anyone who chose "African American/Black," "American Indian/Alaska Native," "Native Hawaiian," "Mexican American/Chicano," "Central/South American," or "Other Latino/Puerto Rican."

4.2.5. Employee Level

Finally, we include controls for employees' *level in the company.* Levels were categorized according to the career ladders or structures at each respondent's company (Simard et al. 2007). Employees were categorized into three levels: low (entry), mid, and high. Mid-level is used as the reference category. Technology, similar to other professional fields, is characterized by vertical segregation, with women being more underrepresented in higher-level positions (Charles and Grusky 2004). Consistent with this trend, women in our sample are more heavily concentrated in the lower-level positions, while men are more concentrated in higher-level positions. Due to the sample size and the somewhat limited number of demographic variables, we are not able to add additional controls to the models.

5. Results

5.1. Summary Statistics

Before turning to regression models, we first explore the bivariate relationships between gender and our dependent and independent variables (see Table 1). Examining our dependent variables, we find that men are significantly more likely than women to identify with the tech profession and marginally more likely to identify with their companies. Men are also significantly more likely to believe their supervisors value their opinions and assign them high-visibility projects. Men are significantly less likely than women to plan to switch career fields in the next twelve months. There are significantly more White men than women in the sample and significantly more Asian women than men. As is common in technology firms in the Silicon Valley, women are more heavily represented among the lower levels compared to the higher levels (Simard et al. 2007).

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[10] We also ran models using the raw difference between individuals' self-ratings and their ratings of successful tech workers as the dependent variable. The overall patterns are consistent with our direction-magnitude interaction models, but our models provide more specific information. We also ran models using a spline variable. Our direction-magnitude interaction models show how the difference between self-ratings and ratings of successful tech workers affects our outcome variables as the difference gets *more negative* for the no-alignment group and *more positive* for the alignment group; spline models show the effect as the difference gets more positive for both groups. Even so, the results of the spline models are largely similar to our models, with the same overall patterns. Models are available upon request.

Table 1. Means and Standard Deviations of Variables used in the Analyses of the Relationship between Alignment and Workplace Outcomes.

Variables	Men	Women
Dependent Variables		
Identify with tech profession [a]	3.83 (0.95)	3.58 *** (1.00)
Identify with company [a]	3.40 (1.06)	3.31 + (1.10)
Supervisor values opinions [a]	3.91 (0.96)	3.74 ** (0.97)
Supervisor assigns high visibility projects [a]	3.64 (1.02)	3.53 * (1.05)
Plan to switch career fields [b]	1.89 (0.97)	2.03 ** (1.01)
Independent Variables		
Cultural Alignment (=1)	0.57	0.38 ***
Cultural Alignment Absolute Value	0.51 (0.40)	0.59 *** (0.48)
Skill Alignment (=1)	0.66	0.53 ***
Skill Alignment Absolute Value	0.58 (0.54)	0.69 *** (0.59)
Race		
White	0.59 (0.49)	0.48 *** (0.50)
Asian	0.36 (0.48)	0.44 *** (0.50)
Other Race	0.06 (0.23)	0.08 (0.27)
Level		
Low (Entry) Level	0.20 (0.40)	0.33 *** (0.47)
Mid-Level	0.55 (0.50)	0.57 (0.50)
High-Level	0.25 (0.43)	0.10 *** (0.30)
N	1048	534

Notes: (standard deviation). + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Bivariate *t*-tests (Simard et al. 2007). N = 1582. [a] Answer choices vary from 1 (not at all descriptive/strongly disagree) to 5 (extremely descriptive/strongly agree). [b] Answer choices vary from 1 (definitely not) to 5 (definitely will). “Don’t know” is coded as missing.

5.2. What Are the Stereotypes About Successful Tech Work?

Figure 1 displays how men and women rated successful tech workers on the cultural and skill set dimension. These ratings reflect the stereotypes individuals hold about successful tech work. As can be seen, men and women hold relatively similar stereotypes, although women hold a *more* stereotypical view of successful tech workers on the cultural dimension, viewing successful tech workers as more geeky, obsessive, etc. The average for men’s ratings of successful tech workers is 2.76 ($\alpha = 0.66$), and women’s ratings average 2.90 ($\alpha = 0.67$) ($p < 0.001$). There is no significant gender difference in how men and women rate successful tech workers on the skill dimension, seeing successful tech workers as equally analytical, questioning, and highly mathematical. On the skill dimension, the average of men’s ratings of successful tech workers is 3.72 ($\alpha = 0.61$), and women’s ratings average 3.77 ($\alpha = 0.60$), an insignificant difference.

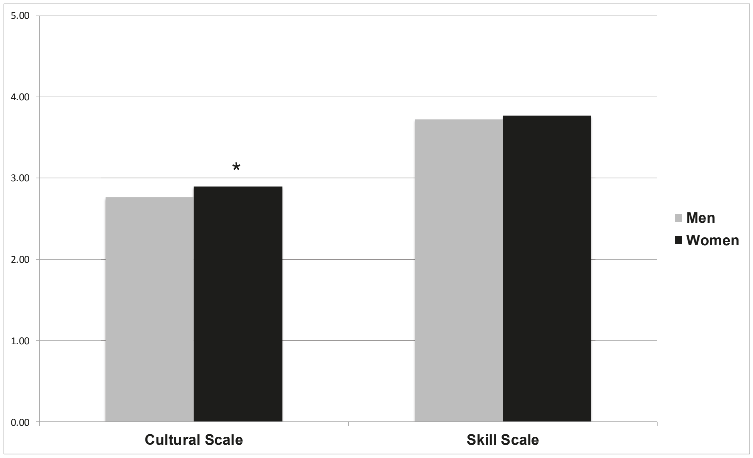

Figure 1. Stereotypes Tech Workers Hold about Successful Tech Work (Simard et al. 2007). N = 1582.

5.3. How Do Individuals Rate Themselves?

Figure 2 displays how men and women rate themselves on the cultural and skill dimensions. As can be seen, women rate themselves significantly lower on both dimensions than men do ($p < 0.001$). The average value on the cultural scale is 2.76 ($\alpha = 0.53$) for men's self-ratings and 2.59 ($\alpha = 0.60$) for women's self-ratings. Thus, men believe they are more obsessive, geeky, etc. than women do. The average skill scale value is 3.83 ($\alpha = 0.59$) for men's self-ratings and 3.62 ($\alpha = 0.64$) for women's self-ratings. Therefore, women tech workers are significantly less likely than men tech workers to think they have analytical quantitative skills, echoing earlier findings from high school and college settings.[11]

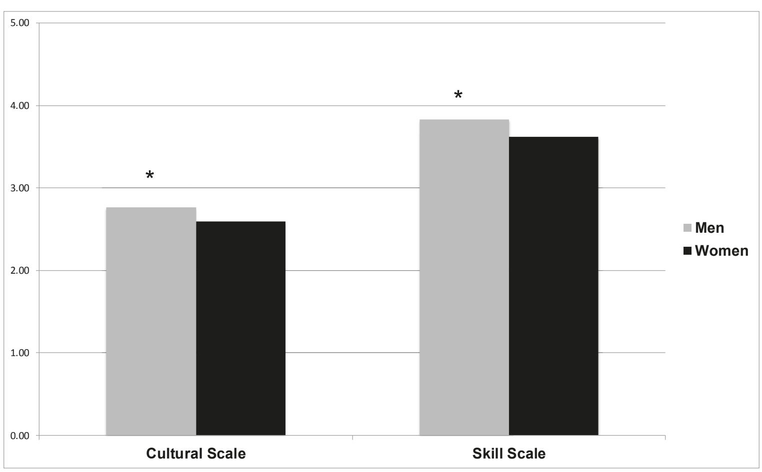

Figure 2. How Tech Workers Rate Themselves on Cultural and Skill Dimensions. N = 1582 (Simard et al. 2007).

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11 Some might wonder if men rate themselves higher on all domains than women. It is worth noting in this regard that the gap between men and women's self-ratings is considerably larger on the cultural domain than on the skill domain. Further, Correll (2001) shows that while men make higher assessments of their mathematical ability, women actually assess their verbal ability higher. This suggests that self-ratings are affected by the gender typing of the domain being considered.

In sum, these measures reveal that men and women hold similar beliefs about the skills required to be a successful tech worker, but women are less likely to believe they themselves exhibit these traits. On the cultural dimension, women are significantly more likely than men to believe that successful tech workers embody obsessive, geeky traits, and they are also significantly less likely than men to believe these traits describe themselves.

5.4. Are Women Less Likely to Align with the Stereotypes of Successful Tech Work?

We now evaluate the extent to which individuals believe they match the cultural image or skill expectation of successful tech workers. Figure 3 plots the percentage of women and men whose image of themselves aligns with their image of successful tech workers. The bar graphs show percentages for the dummy cultural and skill alignment variables. Here we find significant gender differences for both the skill and cultural alignment variables. Only 37% of women demonstrate cultural alignment, rating themselves as greater than or equal to their image of a successful tech worker. In contrast, 56% of men demonstrate positive cultural alignment ($p < 0.001$). Fifty-three percent of women indicate skill alignment, whereas 66% of men have skill alignment ($p < 0.001$). Thus, men are more likely than women to consider themselves similar to successful tech workers in terms of having the cultural traits and skills successful workers posses. A wide chasm exists between men and women's perceptions; men think they have what it takes to be successful, whereas women perceive a gap between themselves and the ideal tech worker, and the gap is especially pronounced on the cultural dimension.

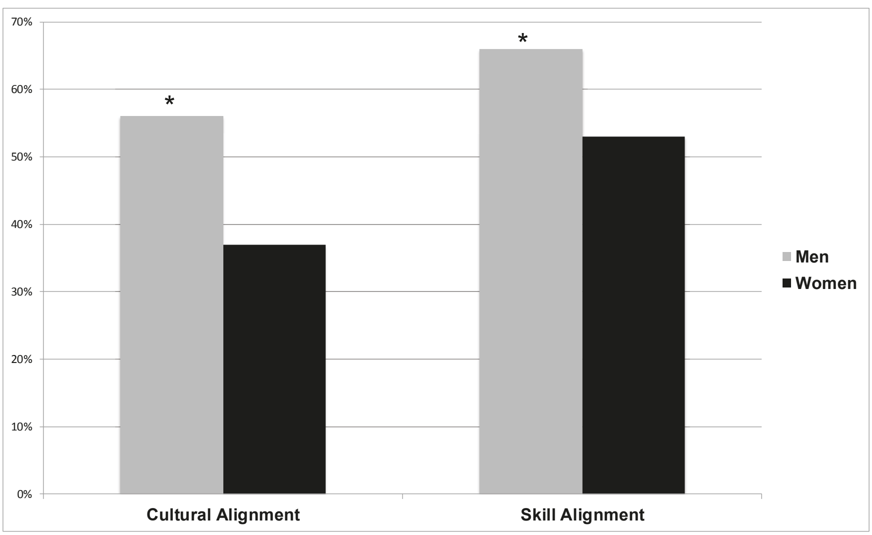

Figure 3. Percent of Women and Men with Cultural and Skill Alignment (Simard et al. 2007). N = 1582. Note: Alignment is defined as a zero or positive gap between self-ratings and ratings of successful tech workers, and non-alignment is defined as a negative gap.

To examine simultaneously the direction and the magnitude of any cultural and skill difference, we plot the magnitude of the gaps, broken down by whether or not individuals see themselves as similar to their image of a successful tech worker on the cultural and skill dimensions.

Specifically, in Figure 4, we graphed the cultural alignment for four different groups: (1) men who do *not* think they match the cultural image of a successful tech worker; (2) women who do *not* think they match the cultural image of a successful tech worker; (3) men who *do* think they align culturally; and (4) women who *do* think they align culturally. We also graphed the skill alignment for men and women who do and do not believe they possess the same skills as successful tech workers. The bar graph shows the extent to which respondents think they are different from successful tech workers; this difference can be in a positive direction (respondents think they are better than the average successful tech worker) or a negative direction (respondents think they are worse than the average successful tech worker).

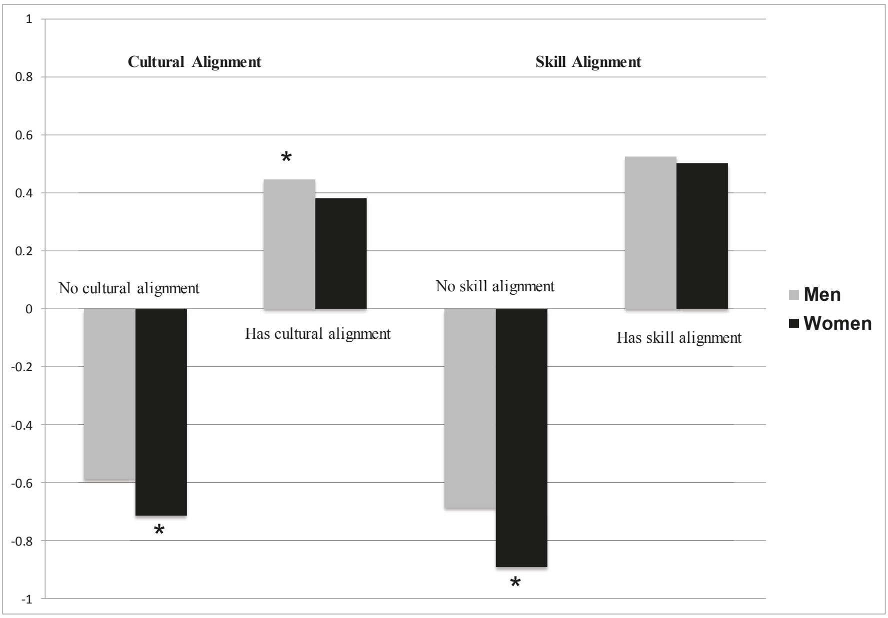

Figure 4. Gap between Self-Ratings and Ratings of Successful Tech Workers by Direction and Gender (Simard et al. 2007). N = 1582. Note: Alignment is defined as a zero or positive gap between self-ratings and ratings of successful tech workers, and non-alignment is defined as a negative gap. The y-axis displays the average successful tech worker rating subtracted from the average self-rating for each group.

When we compare men and women who do *not* perceive themselves as successful on the cultural alignment dimension (bars on the far left of Figure 4), we find that women's absolute value is significantly larger than men's ($p < 0.001$). This means that, among men and women who feel like they do not align, women perceive a large difference between themselves and successful tech workers, whereas this difference is significantly smaller for men. Women more strongly believe they lack the cultural traits valued in their environment.

In contrast, when we compare men and women who *do* consider themselves culturally similar to the successful tech worker (the second set of bars on Figure 4), we find that the gap between self-ratings and ratings of successful tech workers is significantly larger for men ($p < 0.05$). Men are more likely to believe they greatly exceed the cultural standard for success, whereas women in this category only see themselves as equivalent or slightly better than their image of the successful tech worker.

Similarly, when the skill alignment dummy variable equals 0, indicating a perceived lack of skill (third set of bars on Figure 4), women's absolute value is significantly larger than men's ($p < 0.001$). This means that, compared to men who believe they lack skill, women perceive that their lack of skill is much greater, relative to the successful tech worker. However, among people who consider themselves successful on the skill dimension, there is no significant gender difference in absolute value ($p > 0.10$) (right-most bars in Figure 4).

Across our two measures of alignment, among those who do *not* believe they align with the prevailing standard of success, women see themselves as far more deficient than men do when comparing themselves to successful tech workers. However, among those who *do* believe they align, men are more likely than women to see themselves as exceeding the cultural image, but they are no more likely than women to believe they have more skill.[12]

We now turn to regression models that allow us to assess whether these gender differences in alignment are associated with workplace outcomes.

5.5. Analytical Strategy

In the following sections, we estimate a series of ordinary least squares regression models to analyze the effect of cultural and skill alignment on work-related outcomes. We cluster the standard errors by company to account for non-independence. Since these dependent variables are discrete and ordered, we also conducted ordered logistic regressions. Because the results are extremely similar to the OLS models, we present the ordinary least squares estimates here for ease of interpretation. Results from the ordered logistic regressions are available upon request.

We first model the main effects of gender, race, and employee level. Then, we add dummy variables for cultural and skill alignment, which tell us whether alignment is associated with these work outcomes. In the final models, we add absolute value and interaction variables to examine whether the *magnitude* of alignment also matters, or whether the direction of alignment alone is most strongly associated. If the dummy variables are strongest, that means the direction of alignment matters most; if the interactions are significant, that means the magnitude matters as well. Thus, we present two specifications of alignment: one that is direction-only, and the other that includes direction and magnitude.

5.6. Is Alignment Associated with Workplace Outcomes?

We first present a series of models that assess the relationships between alignment (cultural and skill) and our identity measures (identification with the tech profession and identification with the respondent's company). We then turn to models assessing whether alignment is significantly associated with perceptions of supervisor treatment (supervisor values respondent's opinion and supervisor assigns high visibility projects). We then model whether cultural and skill alignment are significantly related to plans to switch career fields. Finally, we assess whether the results presented vary by employee career stage.

Identity models. Model 1 of Table 2 shows the raw gender, race, and employee level effects for identification with the company where the employee works. The non-significant female dummy variable coefficient indicates that there is no significant gender gap in identification with company. There is also no significant effect for company level. However, Asians and "other race" are significantly more likely than Whites to identify with their companies. The Asian result is consistent with literature on Asian culture, particularly regarding STEM fields (Jiménez and Horowitz 2013). In Model 2, we add the cultural and skill alignment dummy variables. Both cultural and skill alignment are significantly associated with identification with one's company, and perhaps unexpectedly, skill alignment is *negatively* associated with company identification. Those who feel they have the skills to succeed are *less* likely to identify with their companies, while those who feel they align culturally are *more* likely to identify.

[12] We also examine effects by company (see Appendix A, Table A6). As the descriptive patterns do not vary substantially across organizations, and since the number of cases for some companies is small, we pool our data across company in the regression models and cluster standard errors by company.

Table 2. Ordinary Least Squares Regression Estimates for the Effects of Cultural and Skill Alignment on Identity Outcomes for Silicon Valley Tech Workers.

	ID with Company			ID with Tech Profession		
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Female (=1)	−0.143 (0.079)	−0.121 (0.078)	−0.118 (0.078)	−0.248 ** (0.051)	−0.196 ** (0.051)	−0.187 ** (0.047)
Asian	0.394 *** (0.047)	0.390 *** (0.046)	0.382 *** (0.046)	0.332 ** (0.073)	0.337 ** (0.069)	0.335 ** (0.069)
Other Race	0.223 * (0.088)	0.205 + (0.087)	0.197 + (0.086)	0.309 *** (0.027)	0.294 *** (.042)	0.292 *** (0.040)
Low-Level	0.168 (0.113)	0.158 (0.111)	0.163 (0.116)	−0.168 ** (0.032)	−0.163 ** (0.038)	−0.159 ** (0.040)
High-Level	0.090 (0.089)	0.094 (0.092)	0.091 (0.091)	0.111 (0.115)	0.090 (0.111)	0.090 (0.111)
Cultural Alignment (=1 when self-rating equals or exceeds successful tech rating)		0.134 *** (0.019)	−0.016 (0.064)		0.163 * (0.057)	0.061 (0.067)
Negative Cultural Self-Assessment, Magnitude (Absolute Value)			−0.216 (0.137)			−0.100 (0.111)
Positive Cultural Self-Assessment, Magnitude (Interaction Term)			0.239 + (0.103)			0.189 (0.125)
Skill Alignment (=1 when self-rating equals or exceeds successful tech rating)		−0.053 * (0.019)	0.098 (0.070)		0.194 *** (0.026)	0.175 (0.112)
Negative Skill Self-Assessment, Magnitude (Absolute Value)			0.083 (0.063)			−0.019 (0.103)
Positive Skill Self-Assessment, Magnitude (Interaction Term)			−0.274 * (0.083)			0.009 (0.129)
Constant	3.192	3.155	3.240	3.705	3.489	3.570
R^2	0.04	0.04	0.05	0.05	0.07	0.07

N = 1582. Note: All models cluster standard errors by company. (robust standard error). + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (Simard et al. 2007).

To assess both the direction and magnitude of alignment on identification, we add the absolute value variables and the interaction terms in Model 3. The cultural alignment interaction is marginally significant and positive, indicating that for those who consider themselves successful on the cultural alignment dimension, the more they exceed the successful tech worker standard, the more they identify with their company.[13] The absolute value variable indicates the effect for those who do *not* feel they align culturally, and the cultural alignment dummy variable indicates the effect of alignment when the absolute value equals zero, or the respondent's self-rating equals their rating of successful tech workers. The skill alignment interaction is significant and negative, indicating that for those who consider themselves successful, the more successful they consider themselves relative to other tech workers, the *less* likely they are to identify with their company.[14] Perhaps people who believe they are overqualified relative to their stereotypes of a successful tech worker seek sources of identification outside the company. Given the higher rate of attrition out of technology from women compared to men (Beede et al. 2011), this is an encouraging finding. Increasing women's cultural alignment with the tech field would presumably increase women's engagement with their companies.

Models 4–6 in Table 2 demonstrate the effects of cultural and skill alignment on identification with the tech profession. As the negative female dummy variable coefficient indicates in Model 4,

13 Technically, the effect for those who believe they align equals the interaction coefficient combined with the absolute value coefficient.

14 While the R^2 is low, our main goal is not to explain all variance in our dependent variables. Instead, we are interested in mechanisms that contribute to the gender gap. As research on the effects of stereotypes shows, even small effects can have large impacts as they cumulate over careers (Martell et al. 1996).

women are significantly less likely than men to identify with the tech profession. Similar to Models 1–3, Asians and "other race" are significantly more likely than Whites to identify. Perhaps unsurprisingly, low-level employees are significantly less likely than mid-level employees to identify with the tech field, while high-level employees do not differ from mid-level employees.

In Model 5, we add the cultural and skill alignment dummy variables. Both skill and cultural alignment are significant and positive, indicating that higher alignment is associated with higher identification with the tech profession. The gender variable also decreases in magnitude with the addition of these two variables, indicating that some of the gender gap in identification is related to the alignment variables, but the gender gap remains significant.

Next, we test whether the *magnitude* of perceived alignment is related to tech identification. We add the absolute value variables and interactions in Model 6. None of the coefficients for these variables are significant, leading us to conclude that Model 5 is the preferred model for identification with tech. For this dependent variable, the direction of alignment (i.e., alignment vs. no alignment) matters more than the magnitude or extent of alignment. The coefficient for the female dummy variable decreases by 21% from Model 4 to Model 5, indicating that about a fifth of the gender gap is associated with cultural and skill alignment.

It is possible the *magnitude* has more of an effect in local environments (e.g., company culture and experiences on teams), while the *direction* has more of an effect on identification with the broader technical culture (e.g., the technology field). To feel identified with the tech field, it may be sufficient for tech employees to merely perceive that their personalities and skills align with expectations, and the magnitude of alignment may matter less than the simple existence of alignment. In contrast, to feel comfortable in local environments (e.g., companies and teams) and to believe that one has what it takes to be successful, the amount of alignment may matter more. That is, individuals may need a more precise estimate of alignment when making sense of self in a specific setting that contains concrete others with whom to compare oneself.[15]

We also added three-way interactions between gender, alignment dummies, and absolute value to assess whether alignment has a stronger or weaker effect on the dependent variables (models not shown). These interactions are not significant. Therefore, men and women place similar value on perceptions of alignment. Lack of cultural and skill alignment do not have a stronger effect for women than for men. Instead, women simply report less cultural and skill alignment than men, thereby lowering their identification with the tech profession.

Supervisor treatment models. We now present models assessing the effect of our alignment variables on perceptions of supervisor treatment. As we detail below, cultural alignment has an even stronger relationship to these dependent variables: women are less likely than men to report that their supervisor values their opinions or assigns them high visibility projects, and controlling for cultural alignment *completely* eliminates these gender gaps. In contrast, skill alignment has almost no impact on these gender gaps (and if anything, it has the opposite effect of what we might expect).

Model 1 of Table 3 shows that women are less likely than men to report that their supervisors value their opinions. Asians are significantly less likely than Whites to report that their supervisors value their opinions. Employee level is not significant. In Model 2, we add the alignment dummy variables and find that the cultural alignment coefficient is significant and positive, while the skill alignment coefficient is insignificant. Further, the female coefficient decreases in magnitude and drops to marginal significance with the addition of the alignment dummies, indicating that much the gender difference in perceptions of supervisor treatment is related to cultural alignment; because women are less likely to believe they align with the cultural profile of a successful tech worker, they are less likely to believe their supervisors value their opinions.

15 It is also possible that the direction-magnitude interaction models (with a dummy variable, absolute value and their interaction) split up the variance in alignment variables so much that it becomes hard to detect independent effects of each component of alignment.

Table 3. OLS Regression Estimates for the Effects of Cultural and Skill Alignment on Perceived Supervisor Treatment of Silicon Valley Tech Workers.

	Supervisor Values Opinion			**Assigns High Visibility Projects**		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Female (=1)	−0.133 * (0.052)	−0.108 + (0.050)	−0.095 (0.049)	−0.081 * (0.031)	−0.053 (0.040)	−0.046 (0.038)
Asian	−0.203 + (0.096)	−0.206 + (0.090)	−0.216 + (0.092)	−0.180 * (0.070)	−0.185 * (0.060)	−0.199 * (0.063)
Other Race	−0.077 (0.104)	−0.097 (0.104)	−0.108 (0.108)	−0.197 (0.153)	−0.222 (0.143)	−0.236 (0.146)
Low-Level	0.003 (0.068)	−0.008 (0.066)	−0.002 (0.065)	0.068 (0.042)	0.053 (0.042)	0.057 (0.049)
High-Level	0.097 (0.071)	0.102 (0.068)	0.100 (0.071)	0.115 (0.089)	0.123 (0.091)	0.120 (0.093)
Cultural Alignment (=1 when self-rating equals or exceeds successful tech rating)		0.158 * (0.043)	−0.121 + (0.056)		0.189 * (0.075)	−0.104 (0.095)
Negative Cultural Self-Assessment, Magnitude (Absolute Value)			−0.305 ** (0.051)			−0.346 * (0.096)
Positive Cultural Self-Assessment, Magnitude (Interaction Term)			0.501 ** (0.090)			0.510 * (0.215)
Skill Alignment (=1 when self-rating equals or exceeds successful tech rating)		−0.057 (0.048)	0.101 (0.058)		−0.093 (0.076)	0.175 * (0.069)
Negative Skill Self-Assessment, Magnitude (Absolute Value)			0.087 + (0.043)			0.158 * (0.051)
Positive Skill Self-Assessment, Magnitude (Interaction Term)			−0.313 *** (0.043)			−0.492 ** (0.093)
Constant	3.957	3.910	4.053	3.672	3.630	3.751
R^2	0.02	0.03	0.05	0.01	0.02	0.06

N = 1582. Note: All models cluster standard errors by company. (robust standard error). + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (Simard et al. 2007).

When we add the absolute value and interaction variables in Model 3, we see that the cultural alignment variables have a strong effect on supervisor treatment. The interaction term is significant and positive, which indicates that for those who consider themselves successful on the cultural dimension, as the gap between themselves and successful tech workers widens, they are *more* likely to report that their supervisor values their opinion. The absolute value variable is significant and negative; for those who are unsuccessful on the cultural dimension, as the gap between themselves and successful tech workers widens, they are *less* likely to report that their supervisor values their opinion.

In contrast, skill alignment has the *opposite* effect. The significant negative skill alignment interaction coefficient indicates that, for those who perceive they have skill alignment, as the absolute value of the difference between self-ratings and ratings of successful tech workers increases, employees are *less* likely to believe their supervisor values their opinions. Those who report they are much stronger in mathematical and analytical skills than their stereotypes of a successful tech worker may be overly confident and difficult to work with. Whatever the reason, lack of skill alignment does not seem to explain why women are less likely than men to feel valued by their supervisors. Instead, lack of cultural alignment is more strongly related to this pattern. The coefficient for the female dummy variable decreases by 29% from Model 1 to Model 3, indicating that much of the gender gap is related to perceptions of alignment. Furthermore, we see that the magnitude of alignment matters in addition to the direction of alignment.

We see similar results for models measuring whether respondents report that their supervisors assign them high visibility projects (Models 4–6, Table 3). The negative coefficient for the female dummy variable in Model 4 shows that women are less likely than men to agree with this statement, and Models 5 and 6 demonstrate that controlling for cultural alignment completely eliminates this gender gap. The coefficient for the female dummy variable decreases by 43% from Model 4 to Model 6 and becomes non-significant. For employees who *do not* align culturally, as the gap between self-ratings and ratings of successful tech workers increases, they are much *less* likely to report that their supervisor assigns high visibility projects. For those who *do* align culturally, as the gap between self and successful tech worker ratings increases, they are much *more* likely to report their supervisor assigns high visibility projects.

Skill alignment shows the same curious pattern as before, where those who perceive they are more skilled than a successful tech worker believe they are less likely to receive high visibility projects from their supervisors. Therefore, perceptions of deviations from the stereotypical image of a successful tech worker, rather than perceived deficiencies in skill, are more strongly associated with gender differences in perceptions of supervisor treatment.[16] Furthermore, other research finds women do receive fewer highly visible, "high-potential" projects relative to men (Silva et al. 2012), suggesting that women's perceptions of supervisor project assignments in the current study may well reflect an accurate representation of their opportunities (rather than being a misguided perception).

Finally, in models not shown, we find that three-way interactions among gender, the cultural alignment dummy, and the cultural alignment absolute value are not significant for the supervisor treatment variables. That is, men and women react similarly to low cultural alignment. Women report less cultural alignment than men, and this is significantly associated with the fact that they are more likely to report negative supervisor treatment.

However, the interaction between gender, the skill alignment dummy, and the skill alignment absolute value variable is negative and significant analyzing whether the respondent feels their supervisor values their opinion ($p < 0.05$, model not shown). In other words, the negative effect of skill alignment on perception of supervisor treatment is not as strong for women relative to men. While for men, higher perceived skill (relative to a successful tech worker) is associated with worse perceived supervisor treatment, this effect is weaker for women.

Turnover intention models. Our final set of models examines the effect of cultural and skill alignment on plans to switch career fields.

In Model 1 of Table 4, there are no significant gender, race, or employee level effects. Recall that the dependent variable asks respondents whether they intend to switch career fields *in the next 12 months.* Since most people do not plan to leave their career field in the near future, the variation in this variable is reduced, making a lack of a main effect for gender, race, and employee level not overly surprising. In Model 2, neither of the alignment variables is significant. However, in Model 3, where the specification of alignment includes both magnitude and direction, we see that cultural alignment has a significant effect on plans to switch career fields. For those who are aligned on the cultural dimension, as the gap between self and successful tech worker ratings increases, they are significantly *less* likely to consider switching career fields in the next 12 months. The reverse is true for those who lack cultural alignment. Therefore, cultural alignment is significantly associated with plans to switch career fields in the near-term future.[17] Skill alignment, by contrast, has virtually no effect. In addition, the magnitude of alignment matters for plans to switch career fields. Given our earlier finding that

16 In studies like this, concerns about endogeneity must also be considered. One alternative explanation for our results could be that women perceive a lack of alignment *because* their supervisors treat them poorly. (In other words, the direction of causality may be reversed.) However, this seems unlikely due to the construction of our alignment variables. Survey respondents were asked to rate the average successful tech worker on a number of attributes, then they rated themselves on those same attributes. Therefore, since we did not directly ask respondents to report perceptions of alignment, but rather constructed the alignment variable from their trait assessments, it seems unlikely that the causal direction could be reversed in this way. While endogeneity can never be ruled out by cross-sectional data, this particular analysis is less susceptible to such concerns due to the way the variables were constructed.

17 Furthermore, in analyses not shown, we added the identification and perception of supervisor treatment variables as independent variables to the model predicting plans to switch career fields and found that identification with the tech profession, perception that supervisor values opinion, and perception that supervisor assigns high visibility projects all significantly predict plans to switch career fields ($p < 0.05$). Therefore, by impacting these variables, alignment also indirectly impacts plans to switch career fields in the next 12 months.

magnitude appears to matter more in local environments (e.g., companies and teams) compared to broader environments (e.g., industry), perhaps people make decisions about leaving a field based on their experiences in their local environment. Whatever the reason, the extent of alignment has a significant impact on turnover intentions.

Table 4. OLS Regression Estimates for the Effects of Cultural and Skill Alignment on Silicon Valley Tech Workers' Plans to Switch Career Fields.

Variables	Model 1	Model 2	Model 3
Female (=1)	0.108 (0.077)	0.115 (0.070)	0.109 (0.071)
Asian	0.102 (0.063)	0.102 (0.061)	0.107 (0.064)
Other Race	0.096 (0.148)	0.092 (0.162)	0.101 (0.159)
Low-Level	0.008 (0.066)	0.007 (0.073)	0.006 (0.073)
High-Level	−0.126 (0.067)	−0.128 (0.067)	−0.126 (0.068)
Cultural Alignment (=1 when self-rating equals or exceeds successful tech rating)		0.033 (0.085)	0.195* (0.079)
Negative Cultural Self-Assessment, Magnitude (Absolute Value)			0.205 *** (0.034)
Positive Cultural Self-Assessment, Magnitude (Interaction Term)			−0.287* (0.103)
Skill Alignment (=1 when self-rating equals or exceeds successful tech rating)		0.010 (0.057)	−0.091 (0.123)
Negative Skill Self-Assessment, Magnitude (Absolute Value)			−0.086 (0.082)
Positive Skill Self-Assessment, Magnitude (Interaction Term)			0.183 (0.127)
Constant	1.878	1.854	1.781
R^2	0.01	0.01	0.02

N = 1582. Notes: All models cluster standard errors by company. (robust standard error). + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (Simard et al. 2007).

These findings have important implications for gender diversity in the tech industry. While most policy efforts to date have involved efforts to enhance women's confidence in their technical skills, our results suggest that efforts focusing on the cultural dimension will likely be more successful. We find that only 37% of women who are in tech jobs have cultural alignment, compared to 56% of men (see Figure 3). However, Model 3 above suggests that if women's cultural alignment were equal to men's, women would be even *more likely* than men to plan to stay in tech careers. Since women enter tech at substantially lower rates than men, retaining women at a higher rate than men could offset some of the gender gap in these fields.

5.7. Does Career Stage Matter?

In the models presented above, we control for tech workers' level in their company. We now ask whether the relationships we have found differ for low, middle, and high-level employees. As we have discussed, stereotypes may have less of an effect on individuals the further they progress in their career. That is, as an individual gains more career experience, she gains more evidence of her skills, which could lessen the effects of stereotypes on career outcomes. In addition, by spending more time in the tech industry, women may develop more realistic, and less stereotypical, images of successful tech workers. By analyzing separate models for employees at different levels, we gain some, albeit limited, insight into this question.

In results not shown, we find that, at higher position levels, there are fewer gender differences in work outcomes. There are no significant differences between high-level women and high-level men in identification with the tech field or in their reports of positive supervisor treatment. However, even among high-level employees, gender gaps in alignment persist. High-level women score significantly lower on cultural alignment compared to high-level men ($p < 0.01$). What differs is that cultural and skill alignment gaps simply are not as strongly associated with work outcomes for high-level women compared to low-level women. Perhaps high-level women have received enough evidence of their ability to draw confidence from other sources. It is also possible that differences between high- and low-level women could reflect differential attrition; women with lower levels of alignment, identification, and/or perceived supervisor treatment may leave the company before reaching the highest levels.

These results are consistent with the idea that as women progress in their careers, the effects of stereotypes become less pronounced. Such differences in gender gaps by level could potentially derive from two mechanisms: either high-level women have higher self-assessments than low-level women on cultural and skill traits, thereby narrowing the gap between their self-assessments and their stereotypes of successful tech workers, or they have less stereotypical assessments of successful tech workers than lower-level women. Either mechanism would lead to higher alignment.

To gain empirical leverage on this question, we analyzed the self and successful tech worker scales separately. On the cultural traits scale, we find no significant difference in how high-level and low-level women rate themselves. (The same is true for high- vs. low-level men.) However, low-level women rate the average successful tech worker significantly higher on the cultural traits scale compared to mid- and high-level women ($p < 0.01$). In other words, low-level women have an inflated view of how geeky, assertive, etc. successful tech workers are compared to high-level women. (There is no significant difference by level among men.) On the skill scale, high-level women rate themselves significantly higher than low-level women ($p < 0.05$), and the same is true for men ($p < 0.01$). Low-level women rate the average successful tech worker marginally higher on the skill scale than mid- and high-level women ($p < 0.10$). (In contrast, there is no difference for men.)

Thus, on the cultural dimension, high-level women do not have a fundamentally different self-image than low-level women; rather, their image of a successful tech worker becomes less stereotypical at higher levels. On the skill dimension, women gain more evidence of their ability (just as men do), while also updating their conception of the average successful tech worker's skills. As women reach higher levels in the tech industry, they revise their image of tech work in more realistic ways; tech workers, after all, are not really spending the bulk of their time playing World of Warcraft in their parents' basement.

6. Summary and Conclusions

In this paper, we introduce the concepts of cultural and skill alignment and ask whether men and women in technical jobs differ in the extent to which they perceive that they have the traits and skills they associate with a successful technical worker. We further examine whether cultural and skill alignment are related to work outcomes such as identifying with the tech field, plans to switch fields, or perceptions of supervisor treatment. While past research has examined how stereotypes shape the movement of young adults into STEM fields, ours is the first study to examine cultural and skill alignment among a sample of men and women in technical jobs.

We find that, while women and men largely agree on the stereotypes about successful tech workers, women hold slightly more stereotypical images of tech workers on the cultural dimension. Furthermore, women are less likely to view themselves as having the cultural traits and skills they associate with successful tech workers. Women are less likely than men to believe they match the stereotypical image of successful tech workers, and this is significantly related to reporting worse work outcomes. Across our dependent variables, we find that cultural alignment is generally more powerful than skill alignment, and cultural alignment explains some of the variance by gender on the identification with the tech profession and supervisor treatment variables. For the supervisor treatment variables in particular, controlling for cultural alignment fully eliminates the gap between men and women. The skill alignment variables either have little effect on the gender gap, or in some cases, skill alignment has the opposite effect of what we might expect. Given the current policy emphasis on improving women's technical skills and confidence, it is surprising that perceptions of skill alignment are less predictive overall in our models than are perceptions of alignment with the cultural image of a successful tech worker.

These findings have important theoretical implications. This is the first paper to clarify the distinction between cultural and skill based forms of alignment and demonstrate their independent effects. We show a connection between women's lack of alignment with the masculinized culture of technology and important work outcomes, such as women's identification with technology and perceptions of supervisor treatment. We further show that these cultural images are often more strongly associated with intentions to leave tech than are skill-based assessments. While cultural alignment is associated with perceived supervisor treatment and plans to switch career fields, skill-based alignment is significantly associated with women's identification with the tech field, leading women to be less likely than men to identify with the field. By analyzing the separate operation of cultural and skill alignment, this paper offers unique insight into the mechanisms that impact gendered outcomes in the technology field.

Furthermore, we find that the simple existence or non-existence of alignment seems to matter more in broader contexts, such as deciding whether or not one belongs in an entire field; in contrast, the extent or magnitude of alignment matters in more localized contexts, such as a company or team. By using direction-magnitude interaction models that examine both the direction and the magnitude of alignment, we are able to tease apart the independent effects of different alignment specifications.

The main practical implication of this study is that if we want to increase the representation of women in STEM fields, we need to attend to cultural alignment in STEM workplaces. Current policies focus primarily on generating young women's interest and skills, thereby slotting women into STEM majors in college, and eventually into STEM careers. Such policies neglect the fact that stereotypes continue to hinder women as they progress in their careers. As long as cultural stereotypes continue to make women feel like they do not fit in, women will be less likely to identify with their professions. Indeed, in their analysis of college students majoring in a STEM field, Cech and colleagues show that students who had less confidence that they fit in a STEM major were less likely to say they intended to enter a STEM career after graduation compared with students who perceived a better fit (Cech et al. 2011). Similarly, the study by Murphy and colleagues demonstrates how male-dominated cultural environments can make female students less likely to feel like they belong, causing even women highly identified with STEM fields to lose interest in pursuing STEM careers (Murphy et al. 2007). Our study shows that even those women who *do* enter a STEM career may be less likely to stay in these fields if they perceive that they lack the cultural traits associated with technical work (e.g., geeky, assertive, and obsessive).

In addition, policies that aim to increase women's human capital by improving their training, restructuring school programs, and targeting women's quantitative and analytical skills, while important, cannot solve the problem by themselves. Even when we compare men and women who have equal perceptions of skill alignment, a cultural divide between the stereotypical view of women and the stereotypical view of successful tech workers disadvantages women, especially at the early stages of their career. Widespread assumptions about who succeeds in tech companies—the masculine-typed geeky coder—continue to proliferate. Our findings suggest that, unless we reshape the cultural images surrounding technology and technical work, women will continue to leave tech jobs in higher numbers than men.

Logically, women's cultural alignment could be increased either by broadening the cultural image of successful tech work, by stressing its collaborative and socially important nature, for example (Cech 2015; Diekman et al. 2010; Diekman et al. 2016), or by urging women to see themselves in ways that align with existing narrow images of tech as geeky, obsessive, etc. Since these images are currently strongly associated with masculinity, the latter approach seems less promising. Policies that broaden the image of a successful tech worker might help increase the retention of women in tech fields. Carnegie Mellon University provides an encouraging example of such change: in 1995, only 7 of 95 students entering the undergraduate program in computer science were women. In 2000, that number had increased to 54 out of 130, or 42% (Margolis and Fisher 2002). The researchers found that the stereotype of computer science majors as geeks "myopically obsessed with computing" discouraged women. Carnegie Mellon broadened the picture of a successful computer science student by encouraging faculty and students to discuss multiple valid ways to be a computer scientist and emphasizing computing's real-world value and connections to other disciplines. Importantly, they did not urge women to change their self-conceptions to fit into the current narrow image of computer science. By changing the cultural image of the computer science major (along with several other changes), Carnegie Mellon succeeded in increasing the representation of women. Tech companies can emulate this example and increase the retention of women by altering the cultural images surrounding tech work.

In a controlled experiment, Cheryan and colleagues found that by simply changing the objects in a computer science classroom from those associated with geeky masculinity (e.g., Star Trek posters) to more gender-neutral objects, college women's interest in computer science increased (Cheryan et al. 2009). However, some technology companies do just the opposite, displaying exactly the kinds of images that Cheryan and colleagues found dampen women's interests (Wynn and Correll 2014). Such stereotype-saturated environments can also influence the treatment of women, such as career mentorship opportunities and salary (Moss-Racusin et al. 2012). While it is hard to change widely shared cultural stereotypes, it is possible for local organizations, such as universities and individual workplaces, to change the images that are present in their environments. Doing so might be especially useful for retaining women in the early stages of their careers.

The dataset for this study comes from seven tech companies in the Silicon Valley. While this area is an important site for technical work, it is not clear if the results would be the same in other regions or even in other companies in the Silicon Valley. Because of our theoretical interests in examining how stereotypes affect men and women tech workers, we sought a sample that would allow us to examine these processes in a heretofore unexamined population. With these unique data of actual tech workers at cutting-edge companies, we believe we gain novel insights into the stereotypes such workers have about successful technical work and how these stereotypes affect men and women tech workers once on the job. Given the increasing importance of technical work for today's economy and the continued dearth of women in these fields, understanding how stereotypes affect the identification and intentions of women and men who are in these fields is of crucial importance.

Furthermore, the findings may apply to other historically male-dominated industries—such as finance, academia, and law enforcement—that continue to narrowly associate success with stereotypically masculine traits (Blair-Loy and Cech 2016). By altering cues in the local environment and changing the prevailing image of a successful worker in these fields, organizations in such industries can potentially increase women's alignment and ultimate retention. Our findings imply that by making the image of success broader and more inclusive, organizations can do more than put women into high-status jobs—they can retain women and enable them to advance.

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Appendix A

Table A1. Rotated Factor Loadings from Principal-Component Factor Analysis on Traits Describing Successful Tech Workers (Simard et al. 2007).

Variables	Factor 1: Intensive Work Commitment	Factor 2: Geeky Personality	Factor 3: Quantitative Skill
Young	0.526	0.451	−0.129
Masculine	0.573	0.384	−0.131
Long Working Hours	0.744	0.111	0.101
Cool	−0.005	0.687	−0.114
Geeky	0.202	0.727	0.170
Highly Mathematical	0.259	0.207	0.608
Obsessive	0.621	0.159	0.212
Assertive	0.644	−0.156	0.051
Analytical	0.029	0.006	0.805
Questioning	−0.004	−0.034	0.682

Table A2. Pearson's Zero-Order Correlation Coefficients from Bivariate Pairs of Cultural Scale Traits Describing Successful Tech Workers (Simard et al. 2007).

Variables	Young	Long Hours	Obsessive	Assertive	Cool	Geeky
Young	1.000					
Long Hours	0.356	1.000				
Obsessive	0.255	0.352	1.000			
Assertive	0.167	0.282	0.333	1.000		
Cool	0.244	0.036	0.128	0.150	1.000	
Geeky	0.266	0.249	0.320	0.117	0.407	1.000

Table A3. Pearson's Zero-Order Correlation Coefficients from Bivariate Pairs of Cultural Scale Traits Describing Self (Simard et al. 2007).

Variables	Young	Long Hours	Obsessive	Assertive	Cool	Geeky
Young	1.000					
Long Hours	0.074	1.000				
Obsessive	0.060	0.225	1.000			
Assertive	0.044	0.172	0.325	1.000		
Cool	0.351	0.095	0.123	0.220	1.000	
Geeky	0.169	0.148	0.278	0.118	0.237	1.000

Table A4. Pearson's Zero-Order Correlation Coefficients from Bivariate Pairs of Skill Scale Traits Describing Successful Tech Workers (Simard et al. 2007).

Variables	Highly Mathematical	Analytical	Questioning
Highly Mathematical	1.000		
Analytical	0.348	1.000	
Questioning	0.207	0.507	1.000

Table A5. Pearson's Zero-Order Correlation Coefficients from Bivariate Pairs of Skill Scale Traits Describing Self (Simard et al. 2007).

Variables	Highly Mathematical	Analytical	Questioning
Highly Mathematical	1.000		
Analytical	0.472	1.000	
Questioning	0.179	0.436	1.000

Table A6. Percent of Men and Women who have Cultural and Skill Alignment by Company.

Company	Variables	Men	Women
Company 1	Cultural Alignment	51%	37% **
	Skill Alignment	55%	50%
	N	127	296
Company 2	Cultural Alignment	58%	36% *
	Skill Alignment	63%	54%
	N	112	28
Company 3	Cultural Alignment	53%	42%
	Skill Alignment	71%	32% **
	N	34	19
Company 4	Cultural Alignment	62%	50%
	Skill Alignment	63%	59%
	N	144	46
Company 5	Cultural Alignment	57%	57%
	Skill Alignment	61%	43%
	N	44	14
Company 6	Cultural Alignment	58%	34% ***
	Skill Alignment	71%	68%
	N	320	68
Company 7	Cultural Alignment	55%	30% ***
	Skill Alignment	67%	57%
	N	267	63

N = 1582. Note: (standard deviation). + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Bivariate t-tests (Simard et al. 2007).

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Article

Queer in STEM Organizations: Workplace Disadvantages for LGBT Employees in STEM Related Federal Agencies

Erin A. Cech [1,*] and Michelle V. Pham [2]

1 Department of Sociology, University of Michigan, 500 S State St, Ann Arbor, MI 48109, USA
2 Population Studies Center, University of Michigan, 500 S State St, Ann Arbor, MI 48109, USA; mvp1@rice.edu
* Correspondence: ecech@umich.edu

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Abstract: Lesbian, gay, bisexual, and transgender (LGBT) individuals in U.S. workplaces often face disadvantages in pay, promotion, and inclusion and emergent research suggests that these disadvantages may be particularly pernicious within science and engineering environments. However, no research has systematically examined whether LGBT employees indeed encounter disadvantages in science, technology, engineering and math (STEM) organizations. Using representative data of over 30,000 workers employed in six STEM-related federal agencies (the Department of Energy, the Environmental Protection Agency, the National Science Foundation, NASA, the Nuclear Regulatory Commission, and the Department of Transportation), over 1000 of whom identify as LGBT, we compare the workplace experiences of LGBT employees in STEM-related federal agencies with those of their non-LGBT colleagues. Across numerous measures along two separate dimensions of workplace experiences—perceived treatment as employees and work satisfaction—LGBT employees in STEM agencies report systematically more negative workplace experiences than their non-LGBT colleagues. Exploring how these disadvantages vary by agency, supervisory status, age cohort, and gender, we find that LGBT persons have more positive experiences in regulatory agencies but that supervisory status does not improve LGBT persons' experiences, nor do the youngest LGBT employees fare better than their older LGBT colleagues. LGBT-identifying men and women report similar workplace disadvantages. We discuss the implications of these findings for STEM organizations and STEM inequality more broadly.

Keywords: STEM; LGBT inequality; Federal Agencies

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1. Introduction

For decades, scholars have documented interactional- and institutional-level processes that perpetuate disadvantages for women and racial/ethnic minorities in science, technology, engineering, and mathematics (STEM). Although these professional arenas are increasingly committed to equality and inclusion [1,2], women and racial/ethnic minorities continue to face marginalization and discrimination in K-12 and college STEM education [3–8] and in STEM workplaces [5,9,10].

Do lesbian, gay, bisexual, and transgender (LGBT) persons experience similar forms of disadvantage within STEM-related environments? Gender and sexuality scholars have argued that hostility toward non-heterosexual identities and non-binary gender expressions often accompanies social contexts dominated by hegemonically masculine gender performances [11–13]. Such biases are rooted in beliefs about *gender* roles; they are reactions to what are presumed to be "normal" or "natural" expressions of gender identity and proper relationships between men and women [12–15]. Emergent research suggests that anti-LGBT bias may be particularly strident in STEM-related environments compared to other professional setting (e.g., [16–18]). As a set of professional arenas that are culturally dominated by hegemonically masculine-typed behavioral norms and interactional styles and that devalue femininity [7,10,19–21], STEM environments likely harbor *heterosexism*, bias and discrimination against LGBT persons that includes marginalization, harassment, and the denial of resources, and *heteronormativity*, a cultural schema that promotes an essentialized male/female sex binary and designates heterosexuality as the only normal sexuality [22,23].

Despite early exploration, researchers have yet to systematically determine whether LGBT workers encounter widespread disadvantages in their day-to-day experiences in STEM-related workplaces. The goal of this paper is to do just that. We use unique, representative survey data to compare the workplace experiences of LGBT employees to their non-LGBT colleagues and to explore whether these inequalities vary by agency, supervisory status, age, and gender. Drawing on ten distinct measures along two different dimensions of workplace experiences—treatment as employees and job satisfaction—this research offers a significant advancement in scholarly understanding of the contours of LGBT inequality in STEM environments.

We study what are, in many ways, "best-case scenario" organizations for LGBT equality and inclusion in science and engineering: STEM-related federal agencies. Unlike the private sector, which is at the whim of organizational, local, and/or state-level anti-discrimination policies, federal agencies have included sexual minorities in their non-discrimination policies since 1998 and transgender persons since 2012. Although heavily hierarchical and bureaucratized accountability structures are not always beneficial for the career advancement of under-represented groups [24], federal agencies are generally recognized as employing organizations with better average diversity outcomes [25–27] and greater equality in leadership [28] and remuneration [29] than organizations in the non-academic private sector.[1] As such, patterns of inequality that we identify within these STEM-related federal agencies are likely present—if not amplified—in STEM organizations in the private sector. Additionally, these are powerful and important organizations for the safety and vitality of the U.S.; thus, it is especially important that all workers in these federal agencies are able to engage and contribute at work to their fullest capacity, regardless of their sexual identity and gender expression.

Six federal agencies are included in our sample: the National Aeronautics and Space Administration (NASA), the National Science Foundation (NSF), the Environmental Protection Agency (EPA), the Department of Energy (DOE), the Nuclear Regulatory Commission (NRC), and the Department of Transportation (DOT). These agencies are described in more detail below. A representative sample of employees from these agencies was included in the U.S. Office of Personnel Management's 2013 Federal Employee Viewpoint Survey (FEVS). FEVS is, to our knowledge, the only large representative workplace survey that includes an LGBT self-identification measure and a range of workplace experience questions. Using these data, we are uniquely positioned to examine workplace experience inequalities by LGBT status in STEM-related agencies.[2]

Unlike much past research on inequality in STEM, ours is an examination of all employees in STEM-related organizations, not an analysis of the experiences of STEM professionals specifically. Workers with STEM training are employed in a great variety of organizations across the labor force—some of which are centrally focused on science and engineering tasks and others (e.g., healthcare or entertainment-related organizations) that are not centrally STEM-focused. The overall culture of an organization can be powerfully shaped by the cultural norms and values of the professional occupations which serve as the raison d'être of that organization [10]. NASA centrally involves

1 Along these lines, a recent Canadian study of pay gaps for gay men found that these gaps were smallest among public-sector workers and largest among private-sector workers [30].

2 We refer to these as "STEM-related agencies" rather than the more common "science agencies" because the former aligns more closely with the actual work done in these agencies (which includes mathematical, engineering, and technical work) and because "STEM" aligns with existing literature on inequality in technoscientific work.

aerospace science and engineering; EPA involves environmental and biological sciences; NSF evaluates and funds basic science, engineering, and math research; NRC is heavily involved with nuclear science and engineering; the DOT is centrally tasked with civil, transportation, and logistics engineering and technology; and the DOE promotes energy sciences. As such, the experiences of employees in these agencies is fundamentally shaped by the cultural norms and practices of STEM in ways that impact their day-to-day workplace experiences, even if employees themselves are not scientists, engineers, mathematicians, or technologists.

As a result of the systemic heterosexism and heteronormativity suggested by previous research on STEM environments [19,31], we expect that LGBT employees in these STEM-related federal agencies will report more negative treatment as employees and be less satisfied with their jobs than their non-LGBT colleagues. We expect that these patterns of inequality may vary depending on the context of each agency. In particular, agencies that principally serve a regulatory function may attract a slightly more politically liberal set of employees who may also be more supportive and inclusive of LGBT colleagues. We also explore whether these inequalities are mitigated for LGBT employees who have advanced in the hierarchy of their organization (i.e., are supervisors), whether recent cultural shifts toward greater rights and inclusivity for LGBT persons manifests as cohort differences in reported workplace experiences, and whether LGBT disadvantages play out differently by gender.

We find that LGBT employees report significantly more negative workplace experiences in these agencies than their non-LGBT colleagues across a number of workplace experience measures. These inequalities appear to be slightly less pronounced in the two regulatory agencies—the EPA and the NRC—relative to the other STEM-related agencies. Contrary to expectations, however, we do not find that inequalities are mitigated for LGBT employees who hold a supervisory role in their agency, nor for the youngest workers, suggesting that these workplace experience disadvantages may neither "get better" with career advancement nor disappear as younger generations of LGBT persons enter the workforce. Finally, we find that both men and women who identify as LGBT face similar workplace experience disadvantages in these agencies.

Examining LGBT inequality as a workplace dynamic is an important approach given the nature of LGBT status biases. Unlike other status characteristics such as gender or race/ethnicity, LGBT status is not reliably visible; LGBT status biases may operate within workplaces even when workers do not know or are not frequently reminded of the LGBT status of their co-workers [32,33]. As such, it is especially useful to study LGBT inequality by examining its entrenchment within STEM-related organizations.

2. Background

Recent research has identified a variety of ways that heterosexism and heteronormativity operate within the U.S. workforce. More than half of U.S. states lack employment discrimination legislation that includes LGBT status and several states are actively seeking to walk back such laws [34]. Within employing organizations, LGBT persons face formal and informal discriminatory policies such as health benefits that exclude transgender persons and same-gender domestic partners [22,35,36]. Informally, LGBT employees frequently encounter wage inequalities, social isolation from colleagues, workplace experience disadvantages, and pressures to downplay or cover their LGBT status (Author cite, [15,37,38]).

Emergent scholarship suggests that these LGBT inequalities are similar, if not more exaggerated, in STEM organizations. Exploratory qualitative work on LGBT employees in STEM organizations has found that they often are isolated from colleagues and feel they work harder than their non-LGBT colleagues to convince others of their competence as STEM professionals [16,39]. Studies of academic settings have found that LGBT students and faculty in STEM are more likely than LGBT persons in other disciplines to report discomfort with the campus climate and fear harassment and physical violence on campus [18,22,40,41].

Despite this early research, we know very little about the experiences of LGBT-identifying workers in science and engineering environments. This paper seeks to fill this void by comparing

LGBT and non-LGBT colleagues in the same STEM-related organizations across an array of workplace experiences. As we discuss in the conclusion, the results presented here are likely applicable to STEM organizations across the labor force—even organizations that, like the federal agencies we study, have non-discrimination policies that include sexual identity and gender expression.

2.1. STEM-Related Federal Agencies

Six federal agencies are included in our study. To provide context for our analysis, we briefly describe the origins and goals of each agency.

Environmental Protection Agency (EPA): Sparked by the physical and political fallout of the Santa Barbara oil spill in 1969, president Nixon formed the Environmental Protection Agency (EPA) in 1970 [42,43]. The EPA is a regulatory agency whose mission it is to protect human health and the environment and to "ensure compliance with environmental laws passed by Congress, state legislatures and tribal governments" [44]. The EPA works to make the United States air, water, and land cleaner and safer through policies such as the Clean Water and Clean Air Acts [45].

Nuclear Regulatory Commission (NRC): In the wake of the first atom bomb detonation in 1945 and the Cold War arms race that ensued, the federal government saw a need to regulate nuclear materials and find civilian uses for nuclear energy. The Atomic Energy Commission (AEC) was created in 1946 to regulate and promote nuclear power. However, the AEC depended on the nuclear industry to produce data for them and to regulate themselves [46,47]. To address the inherent conflict of both promoting and regulating the nuclear industry, the 1974 Energy Reorganization Act split the AEC into the Nuclear Regulatory Commission (NRC) and the Energy Research and Development Agency (ERDA) [48].[3] The NRC now oversees the nuclear industry by regulating nuclear materials and creating and enforcing nuclear safety requirements [47].

Department of Energy (DOE): The energy shortage of the 1970s demonstrated the need for federal policy regarding energy creation and transmission, which had largely been left to the private sector [50,51]. President Carter signed the Department of Energy into action in 1977 [52]. The new agency's responsibility was to "[advance] the national, economic, and energy security of the United States; [promote] scientific and technological innovation in support of that mission; and [ensure] the environmental cleanup of the national nuclear weapons complex" [50]. The Department of Energy is responsible for research and development of energy technologies, energy conservation and regulation planning, and energy data collection and analysis [48]. Currently, clean energy research and development stands as the DOE's highest priority [53].

National Aeronautics and Space Administration (NASA): Russia's launch of the satellite Sputnik sparked a fervor in the U.S. government for aerospace research [54–56]. President Eisenhower signed the National Aeronautics and Space Act on 29 July 1958 to establish an agency that would "pioneer the future in space exploration, scientific discovery and aeronautics research" [56,57]. Building on the early accomplishments of its Apollo program, NASA is currently responsible for continued space and exploration research and works alongside the space programs of other nations and the nascent for-profit space exploration industry [57].

National Science Foundation (NSF): Congress signed a bill in 1950 to establish the National Science Foundation, an agency intended to facilitate the perpetuation of the wartime pace of scientific and engineering advancements during times of peace [58]. The NSF's central goals are to support research and education in science and engineering [59]. From its inception, the mission of NSF has dictated that scientists and engineers be in charge of the agency and that patenting guidelines are developed and managed by the foundation itself [60,61].

Department of Transportation (DOT): The transportation infrastructure played an important role in the post-World War II economic boom [62]. By the 1960s, billions of dollars were being

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[3] The Energy Research and Development Agency was absorbed into the DOE upon its creation in 1977 [49].

spent across eleven transportation-related agencies that dealt with differing facets of transportation management [62]. Congress adopted the Department of Transportation Act in 1966 to consolidate these efforts into one agency [63]. The new agency was intended to "serve the United States by ensuring a fast, safe, efficient, accessible and convenient transportation system that meets our vital national interests and enhances the quality of life of the American people, today and into the future" [64]. DOT is currently responsible for creating and coordinating wide-reaching transportation policies and programs across the U.S. [64].

Although the climate for LGBT-identifying employees may vary across these agencies, they—like all federal employees—are protected by anti-discrimination policies that are inclusive of sexual minority and gender expression. Furthermore, each of these agencies has an LGBT-specific Employee Resource Group (ERG) that provides networking, advocacy, and social support for LGBT employees and allies.

2.2. Hypotheses

Based on research discussed above on the experiences of LGBT persons in the workforce generally and in STEM specifically, we expect that LGBT-identifying employees in STEM-related federal agencies will report significantly less positive workplace experiences than their non-LGBT colleagues. We focus on two specific dimensions of workplace experiences, shown to be important in previous research on LGBT workplace inequality [32,65–67]: respondents' perceived treatment as employees (e.g., whether they feel like their work is respected and that they are supported by their co-workers) and their work satisfaction (e.g., whether they are personally satisfied with their job and the extent to which they feel empowered at work). Due to processes of heterosexism and heteronormativity discussed above, we expect that LGBT persons will report significantly less positive treatment as employees, and be less satisfied with their work compared to their non-LGBT colleagues.

Hypothesis 1: *LGBT-identifying employees will report worse workplace experiences than their non-LGBT colleagues, net of agency, gender, racial/ethnic minority status, age cohort, tenure, and supervisory status*.

Support for LGBT equality and inclusion varies drastically across the two dominant political parties in the U.S. As entities that work in and around partisan politics, we might expect that some of this partisanship might play out within the context of the federal agencies themselves. However, as federal agencies, the six organizations that we study are bipartisan by definition and decree. The top-level leadership of several of them is purposefully comprised of an equal balance of democratic and republican appointed executives.

Although none of them are "conservative" or "liberal" agencies with corresponding views on LGBT equality, we suspect that the average workplace experiences for LGBT employees may vary depending the politicization of the core work of the agency. Specifically, there may be differences between the experiences of LGBT employees who work in agencies that principally serve a *regulatory* function (i.e., EPA and NRC), versus those that work in agencies that serve a number of other functions. Government regulation *itself* is politicized: conservative political leaders and legislators have called for broad-scale deregulation, and conservative voters tend to be deeply unsupportive of expanding government regulation [68,69].[4] As such, we expect that the regulatory agencies in our sample may attract a slightly more politically and socially liberal set of employees than the other agencies. These more liberal pro-regulation employees may thus be more supportive of LGBT rights and inclusion [71,72] than the average employees in other federal agencies.

[4] For instance, in recent Pew polls, 76% of Republicans say that the government regulation of business does more harm than good (compared to 41% of Democrats) while 64% of Democrats (compared to only 28% of Republicans) believe that environmental protection should be strengthened [70].

Hypothesis 2: *LGBT employees who work in regulatory agencies (i.e., EPA and NRC) will report more positive workplace experiences than LGBT employees who work in other STEM-related agencies, net of age cohort, supervisory status, gender and racial/ethnic minority status*.

Previous research on LGBT persons in the workforce has suggested that those who occupy leadership positions in their organizations have more social power and are more able to be open about their LGBT status than those who are lower in the organizational hierarchy and thus more vulnerable [65,66].[5] As such, we expect that LGBT persons who are supervisors may be comparatively insulated from the effects of LGBT status biases and report significantly more positive workplace experiences compared to LGBT persons who do not hold a supervisory role in their organization:

Hypothesis 3: *LGBT employees who are supervisors report significantly more positive workplace experiences than their LGBT colleagues who are not supervisors, net of agency, age cohort, tenure, gender and racial/ethnic minority status*.

Over the last several decades, public views on sexual minorities and transgender individuals have changed dramatically [73]. Although over half of Americans express some level of disapproval toward sexual minorities [74], younger cohorts have entered the workforce during a time when blatant heterosexism is on the decline and state and local legislation has become more equitable overall for LGBT-identifying persons. Older LGBT-identifying federal employees experienced a different work environment in past decades. Up until the 1980s, LGBT persons were regularly denied the security clearances so often required of work in science and engineering agencies and were subject to invasive questioning in security clearance applications through the 1990s [75]. Given these political and social changes, we might expect that the youngest cohorts of LGBT-identifying workers may report systematically more positive work experiences than their older colleagues. Even if older LGBT colleagues face a qualitatively better work environment now than in the past, their views on their current workplace experiences may be colored by past experiences of prejudice. As such, we expect there to be a significant and negative interaction effect between age cohort and LGBT status, meaning that younger LGBT persons have more positive workplace experiences than older LGBT colleagues.

Hypothesis 4: *Older LGBT employees will report significantly more negative workplace experiences than younger LGBT employees, net of agency, gender, racial/ethnic minority status, tenure, and supervisory status*.

If, however, the LGBT * age cohort interaction terms are insignificant, this would indicate that younger cohorts of LGBT persons are not generally better off than their older LGBT colleagues.

Finally, we examine whether these LGBT inequalities vary by gender. Existing scholarship does not suggest an obvious set of relationships. For men, LGBT status likely undermines workplace experiences, both because of negative status biases toward LGBT persons in general and the cultural association of gay, bisexual, and transgender men with femininity [22] that is devalued in STEM environments [19]. The pattern among women is less clear. On the one hand, lesbian, bisexual, and transgender women are culturally associated with masculinity, which may mean that they are taken more seriously in STEM-related environments and have better work experiences [19]. On the other hand, LGBT-identifying women's divergence from normative or "natural" gender roles may mean that they encounter more negative treatment and have less work satisfaction than other women in their agencies. We investigate whether there are gendered patterns in these LGBT inequalities by comparing LGBT and non-LGBT men and women separately. The results of this analysis shed light on gender processes in STEM environments more generally by helping to disentangle whether gender biases are

[5] Along similar lines, interviews with sexual minority graduate students in engineering suggested that they felt more comfortable being open about their sexual identity as teaching assistants than they were as undergraduate students [19].

principally an issue of the devaluation of *femininity* (which would reflect LGBT biases for men but no effect—or possibly a benefit—of LGBT status for women) or broader processes related to the norms and expectations of the gender structure more broadly.

3. Methods

We use data from the 2013 Federal Employee Viewpoint Survey (FEVS) for these analyses. FEVS is a representative survey of employees in federal agencies in the U.S. conducted by the Office of Personnel Management (OPM). In 2012, OPM added a question about LGBT status to the FEVS. Although FEVS has limitations in that it is cross-sectional and does not (for reasons of confidentiality) include details on respondents' occupation or specific positions of employment, it is the only available dataset that offers the ability to assess the workplace experiences of LGBT persons in STEM-related organizations using representative data.

The full 2013 FEVS sample contains 376,577 employees.[6] For this analysis, we use the 37,219 respondents who are employed in the six STEM-related agencies. We use multiple imputation (20 multiply-imputed datasets) to handle missing data on all measures except LGBT status[7] and all models are weighted with the OPM-provided proportional weight "postwt".

3.1. Variable Operationalization

Table 1 provides information on specific question wording and scale construction. LGBT status, the focal independent variable, was created by OPM out of a question that asked respondents: "Do you consider yourself to be one of the following (mark all that apply):" "Heterosexual or Straight", "Bisexual", "Gay or Lesbian", "Transgender", and "Prefer not to say". Respondents who selected bisexual, gay or lesbian, or transgender were coded as LGBT. Respondents who marked "prefer not to say" (12% of the sample) were excluded from the analysis.

Table 1. Operationalization of workplace experience dependent variables.

	Perceived Treatment as Employees
Work Success is Fostered	"I feel encouraged to come up with new and better ways of doing things", "I am given a real opportunity to improve my skills in my organization", "I have enough information to do my job well", and "My talents are used well in the workplace". (1 = [neg]ative to 3 = [pos]itive; α = 0.820)
Transparent Evaluations	"My performance appraisal is a fair reflection of my performance", "My supervisor/team leader provides me with constructive suggestions to improve my job performance", and "Discussions with my supervisor/team leader about my performance are worthwhile", (1 = neg to 3 = pos; α = 0.816)
Adequate Resources	"I have sufficient resources to get my job done", "My workload is reasonable", and "My training needs are assessed". (1 = neg to 3 = pos; α = 0.657)
Respected by Supervisor	"My supervisor/team leader listens to what I have to say", "My supervisor/team leader treats me with respect", and "My supervisor/team leader provides me with opportunities to demonstrate my leadership skills". (1 = neg to 3 = pos; α = 0.852)
Diversity Supported	"My supervisor/team leader is committed to a workforce representative of all segments of society", "Policies and programs promote diversity in the workplace", "Prohibited Personnel Practices are not tolerated", and "Managers/supervisors/team leaders work well with employees of different backgrounds". (1 = neg to 3 = pos; α = 0.798)

6 FEVS was administered to a random sample of all permanent, non-seasonal employees of 37 large agencies and 45 independent agencies. The 2013 response rate was 48.2%, which is a typical response rate for workplace surveys [76].

7 The Stata "chained" command was used to produce the 20 imputed datasets. Seventeen percent of responses were missing on the diversity support measure and 16 percent were missing from the meritocratic organization measure. All other measures had less than 7 percent missing.

Table 1. *Cont.*

Perceived Treatment as Employees	
Workplace Satisfaction	
Personal Satisfaction from Work	"I like the kind of work I do", "My work gives me a feeling of personal accomplishment", and "The work I do is important". (1 = neg to 3 = pos; α = 0.723)
Satisfaction with Working Conditions	"Employees are protected from health and safety hazards on the job", "Physical conditions allow employees to perform their jobs well", "My organization has prepared employees for potential security threats", and "I recommend my organization as a good place to work". (1 = neg to 3 = pos; α = 0.659)
Employee Empowerment	"Creativity and innovation are rewarded", "Employees have a feeling of personal empowerment with respect to work processes", "Employees are recognized for providing high quality products and services", and "Supervisors/team leaders in my work unit support employee development". (1 = neg to 3 = pos; α = 0.844)
Satisfaction with Procedures	"How satisfied are you with the recognition you receive for doing a good job?" "How satisfied are you with your involvement in decisions that affect your work?" "How satisfied are you with your opportunity to get a better job in your organization?" and "How satisfied are you with the information you receive from management on what's going on in your organization?" (1 = neg to 3 = pos; α = 0.835)
Overall Job Satisfaction	"Considering everything, how satisfied are you with your job?" (1 = neg to 3 = pos)

We examine two dimensions of workplace experiences: treatment as employee measures and work satisfaction measures (also see [32]. The range of measures we include are important: some of them (e.g., job satisfaction, respected by supervisor) are less dependent on one's particular occupation or hierarchical position than others (e.g., adequate resources). This range also allows us to understand whether patterns of inequality seem to coalesce around only one type of workplace experience inequality or extend across a wider array of issues.

The individual measures, and the variables that were used to make up the scales, are detailed in Table 1. In the original FEVS instrument, respondents were asked their level of agreement with each statement on a 1–5 scale (1 = "strongly disagree", 2 = "disagree", 3 = "neither agree nor disagree", 4 = "agree", and 5 = "strongly agree"). Questions related to work satisfaction were asked with a parallel 1–5 scale ranging from "very dissatisfied" to "very satisfied". In order to help protect confidentiality, OPM recoded the 1–5 response values on each question into a 1–3 positive/negative response range, where 3 = positive (agree or strongly agree; satisfied or very satisfied), 2 = neutral (neither agree nor disagree; neither satisfied nor unsatisfied), and 1 = negative (strongly disagree or disagree; very dissatisfied or dissatisfied). The index measures below were divided by the number of measures in the index in order to retain a 1–3 value range.

3.2. Controls

Our models control for as wide a range of demographic and employment variables as is available in the data. Specifically, we control for gender (1 = woman, 0 = man), racial/ethnic minority (REM) status (1 = identify as African-American, Asian, Hispanic or Latino, Native American and/or other nonwhite identity; 0 = identifies as white, non-Hispanic), tenure in one's agency (1 = 5 or fewer years, 2 = 6–14 years, 3 = 15 or more years), supervisory status (1 = supervisor, manager, or executive; 0 = non-supervisor or team leader), and age cohort (1 = under 40 years; 2 = 40–49 years; 3 = 50–59 years; 4 = 60 years or above). Due to concerns about possible identifiability and loss of confidentiality, the Office of Personnel Management does not provide educational background level or occupational category in FEVS, nor does it grant restricted-use access to such data. As such, we are not able to determine whether individual respondents in these agencies are employed in STEM occupations or have STEM degrees.

3.3. Analytic Strategy

Means and standard errors for all respondents and for LGBT and non-LGBT persons separately are included in Table 2. To test our hypotheses, we use OLS regressions for all but one of our dependent measures. Because overall job satisfaction is a single-question measure with a 1–3 value range, we use an ordered logistic regression model for that measure. We test the first hypothesis with models that include the LGBT identity measure, alongside controls for gender, REM status, supervisor status, employment tenure, age cohort, and agency. For the second hypothesis, we re-run this set of models with interaction terms between LGBT status and each of the agencies, including these interaction terms in the models one at a time. Hypotheses 3 and 4 are tested by adding to the previous models interaction terms for LGBT status X supervisor status and LGBT status X age cohort, respectively. Finally, to investigate possible differences in the effect of LGBT status by gender, we present the LGBT coefficients for each outcome measure in models ran separately for men and women.

Table 2. Univariate and Bivariate Statistics for LGBT and non-LGBT Respondents.

	ALL (N = 37,219)		LGBT (N = 1042)		Non-LGBT (N = 36,177)		*p*
	Mean	**SE**	**Mean**	**SE**	**Mean**	**SE**	
LGBT	0.028	0.001	n/a		n/a		
Female	0.369	0.003	0.379	0.016	0.369	0.003	
Racial/Ethnic Minority	0.279	0.002	0.251	0.014	0.279	0.002	*
Supervisor	0.184	0.002	0.183	0.012	0.184	0.002	
Age cohort	2.495	0.005	2.293	0.030	2.500	0.005	***
Tenure	2.318	0.004	2.219	0.025	2.321	0.004	***
Treatment as Employee							
Success fostered	2.513	0.003	2.394	0.021	2.517	0.003	***
Transparent evaluations	2.548	0.003	2.438	0.022	2.551	0.003	***
Adequate resources	2.291	0.003	2.146	0.021	2.295	0.003	***
Respected by supervisor	2.709	0.003	2.635	0.019	2.711	0.003	***
Diversity supported	2.592	0.003	2.489	0.019	2.594	0.003	***
Work Satisfaction							
Personal satisfaction	2.768	0.002	2.710	0.015	2.769	0.002	***
Working conditions	2.705	0.002	2.613	0.015	2.708	0.002	***
Employee empowerment	2.357	0.003	2.243	0.022	2.360	0.003	***
Procedure satisfaction	2.300	0.003	2.160	0.021	2.304	0.003	***
Job satisfaction	2.593	0.004	2.446	0.025	2.597	0.004	***
Agencies							
EPA	0.084	0.001	.152	0.011	0.082	0.001	***
NRC	0.053	0.001	0.053	0.007	0.053	0.001	
NSF	0.018	0.001	0.027	0.005	0.018	0.001	
NASA	0.218	0.002	0.168	0.012	0.220	0.002	
DOT	0.487	0.003	0.464	0.015	0.487	0.003	
DOE	0.140	0.002	0.136	0.011	0.140	0.002	

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test comparing LGBT and non-LGBT respondents).

4. Results

Table 2 provides means and standard errors for the demographic and workplace experience measures for all respondents and separately by LGBT status. Just under three percent (2.8%) of our sample identifies as LGBT. This is noticeably lower than national estimates that 3.4% of the U.S. population identifies as LGBT [65], suggesting that LGBT persons are under-represented in these STEM-related agencies relative to their representation in the U.S. population in general. Compared to non-LGBT respondents, there is a significantly lower proportion of REMs among the LGBT sample and the LGBT sample is typically younger and has a shorter tenure. In these bivariate statistics, LGBT persons have significantly more negative workplace experiences across all of the measures included here. The multivariate analyses below will test whether these differences remain net of variation in age, tenure, supervisory status, gender and race/ethnicity. Table 2 also provides the proportion of the total sample are employed in the six different agencies. Appendix A Table A1 provides the representation of LGBT persons in each agency, ranging from a high of 5.0% at the EPA and a low of 2.2% at NASA.

We hypothesized above that LGBT-identifying employees would report worse workplace experiences than their LGBT colleagues in the form of more negative treatment and worse job satisfaction. Table 3 presents the results of the OLS and ordered logit models predicting the workplace experience measures with LGBT status and controls. As expected, LGBT-identifying employees report more negative workplace experiences along a variety of different measures: they are less likely than their non-LGBT colleagues to report that their success is fostered, that they have adequate resources, that their organization supports diverse workers, and (marginally) that they have transparent evaluations in their workplace. We also find substantial differences in job satisfaction: LGBT employees report significantly lower satisfaction with employee empowerment and organizational procedures in their agency, and lower overall job satisfaction than their non-LGBT colleagues. They are also marginally significantly less likely to report personal satisfaction with their work and satisfaction with the working conditions in their organization. On average, these effect sizes are about a tenth of a point on a three-point scale (1 = negative to 3 = positive).

Table 3. OLS and Ordered Logistic Regression Models Predicting Workplace Experience Measures with LGBT Status and Controls (N = 37,219).

	Treatment as Employees Measures									
	Success Fostered		**Transparent Evaluations**		**Adequate Resources**		**Respected by Supervisor**		**Diversity Supported**	
	B	***S.E.***	**B**	***S.E.***	**B**	***S.E.***	**B**	***S.E.***	**B**	***S.E.***
LGBT	−0.115 *	0.046	−0.084 †	0.043	−0.162 ***	0.046	−0.074	0.046	−0.147 *	0.066
Female	0.035 **	0.013	0.005	0.013	0.011	0.013	−0.031 *	0.014	−0.029 *	0.012
REM	0.008	0.015	−0.017	0.014	0.081 ***	0.015	−0.035 *	0.014	−0.134 ***	0.014
Supervisor	0.203 ***	0.014	0.130 ***	0.014	−0.048 **	0.016	0.153 ***	0.011	0.216 ***	0.011
Tenure	−0.060 ***	0.011	−0.075 ***	0.011	−0.066 ***	0.010	−0.041 ***	0.010	−0.079 ***	0.009
EPA	−0.018	0.017	0.067 ***	0.017	−0.173 ***	0.017	0.056 ***	0.015	0.058 ***	0.015
NSF	0.064 *	0.027	0.079 **	0.028	−0.088 **	0.029	0.029	0.026	0.037	0.025
NASA	0.267 ***	0.011	0.226 ***	0.012	0.177 ***	0.012	0.164 ***	0.010	0.246 ***	0.010
NRC	0.185 ***	0.015	0.149 ***	0.017	0.218 ***	0.017	0.111 ***	0.014	0.187 ***	0.014
DOT	0.004	0.015	0.071 ***	0.015	0.046 **	0.014	0.022	0.014	0.019	0.013
Constant	2.485 ***	0.027	2.577 ***	0.027	2.369 ***	0.025	2.750 ***	0.025	2.69 ***	0.022
	Workplace Satisfaction Measures									
	Personal Satisfaction		**Satisfactory w/Working Conditions**		**Employee Empowerment**		**Procedures Satisfaction**		**Overall Job Satisfaction ˆ**	
	B	***S.E.***	**B**	***S.E.***	**B**	***S.E.***	**B**	***S.E.***	**B**	***S.E.***
LGBT	−0.049 †	0.026	−0.080 †	0.045	−0.115 *	0.046	−0.140 **	0.050	−0.379 *	0.153
Female	0.011	0.008	0.002	0.011	0.037 **	0.013	0.017	0.013	0.078 †	0.044
REM	0.018 *	0.008	0.028 *	0.012	0.042 **	0.015	0.046 **	0.015	0.081 †	0.048
Supervisor	0.098 ***	0.009	0.128 ***	0.011	0.274 ***	0.015	0.243 ***	0.016	0.505 ***	0.054
Tenure	−0.029 ***	0.006	−0.058 ***	0.008	−0.102 ***	0.011	−0.092 ***	0.010	−0.229 ***	0.035
EPA	−0.002	0.012	0.035 *	0.011	0.040 *	0.017	−0.037 *	0.016	−0.020	0.053
NSF	0.044 *	0.019	0.064 ***	0.017	0.057 *	0.028	0.003	0.027	0.105	0.093
NASA	0.096 ***	0.008	0.169 ***	0.008	0.386 ***	0.012	0.303 ***	0.011	0.695 ***	0.041
NRC	0.073 ***	0.012	0.152 ***	0.010	0.267 ***	0.017	0.233 ***	0.016	0.514 ***	0.061
DOT	0.059 ***	0.010	−0.014	0.011	0.009	0.015	0.030 *	0.015	0.279 ***	0.049
Constant	2.728 ***	0.015	2.686 ***	0.020	2.296 ***	0.027	2.280 ***	0.026	N/A	N/A

Notes: DOE is the comparator category for the agency. REM = Racial/ethnic minority status. Columns report unstandardized coefficients (and Std. Errors) from regression models. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test), ˆ indicates ordered logit models; all other models are OLS regressions.

Overall, these results indicate workplace experience inequalities for LGBT-identifying employees across a wide range of treatment and satisfaction measures (supporting H1). Figure 1 presents the mean values on each workplace experience measure for LGBT and non-LGBT workers, respectively. Error bars represent 95% confidence intervals ($\pm 1.96 \times$ SE). The asterisks indicate the significance of the difference between LGBT and non-LGBT coworkers on each measure, net of controls (significance values taken from Table 3).

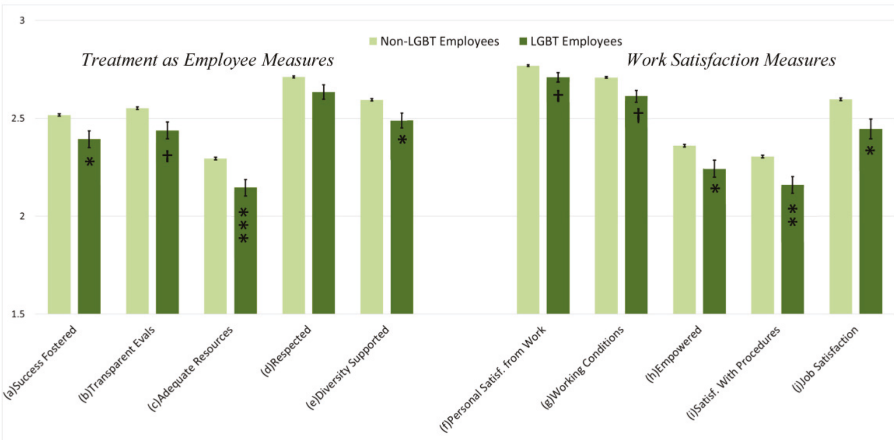

Figure 1. Workplace Experiences among Non-LGBT and LGBT Employees. *Height* of the columns indicates the means for LGBT and non-LGBT employees, respectively (error bars = 95% C.I.s). *Asterisks* indicate significance of LGBT status net of variation by gender, REM status, tenure, age category, and agency (* $p < 0.05$, ** $p < 0.010$, *** $p < 0.001$, based on two-tailed tests; 1 = negative, 2 = neutral, 3 = positive). See Table 3 for significance levels of the direct comparison of LGBT and non-LGBT workers.

Although the STEM-related federal agencies in our sample share anti-discrimination regulations and procedures, we expect there to be variation in the experiences for LGBT persons across these agencies. In particular, we expect that LGBT employees will do slightly better in agencies that served a primarily regulatory purpose, as workers with conservative anti-regulation political views (which are correlated with less positive views of LGBT equality) may be likely to self-select out of those agencies.

To test Hypothesis 2, we predicted the workplace experience measures with an interaction term between LGBT status and each agency indicator. The LGBT*agency measures were included in the models one at a time. Figure 2 summarizes the patterns of significance for these interaction terms. Specifically, the figure presents the direction and level of significance of the interaction term between that agency and LGBT status that reach at least marginal statistical significance ($p < 0.10$). A significant and positive interaction term would indicate that LGBT respondents at that agency have significantly more positive experience on that measure compared to LGBT respondents in other agencies. Appendix A Table A2 presents the coefficients, standard errors, and p-values for each of these interaction terms.

The results are in the expected direction: LGBT respondents employed in the EPA are significantly more likely to report that they have adequate resources and to be satisfied with their working conditions, and marginally more likely to report satisfaction with organizational procedures, compared to LGBT persons in the other STEM-related agencies. The Nuclear Regulatory Commission also promotes more positive workplace experiences for LGBT persons compared to other agencies along several dimensions: LGBT persons in the NRC report more transparent evaluations, more support for diversity, and, marginally, more adequate resources and more satisfaction with working conditions and procedures, compared to LGBT employees in other agencies. NSF LGBT employees reported significantly higher levels of employee empowerment and NASA LGBT employees reported greater resources than LGBT employees at other agencies. On the flip side, LGBT employees in the DOE are significantly less likely to report adequate resources and more negative working conditions than LGBT employees at other agencies.[8]

	EPA	NRC	NASA	NSF	DOT	DOE
Treatment as Employee Models						
Success fostered		(pos) †				
Transparent evaluations		(pos) *				
Adequate resources	(pos) *	(pos) †	(pos) *			(neg) *
Respected by supervisor						
Diversity supported		(pos) **				
Work Satisfaction Models						
Personal satisfaction		(pos) **				
Working conditions	(pos) *	(pos) †				(neg) *
Employee empowerment				(pos) *		
Procedure satisfaction	(pos) †	(pos) †				
Job satisfaction ^						

Figure 2. Significance Level and Direction of LGBT*Agency Interaction Terms, for Regulatory (EPA, NRC) and Non-Regulatory (NASA, NSF, DOT, DOE) Agencies. Note: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test). Only significant interaction terms are presented; all other interactions terms have $p > 0.10$. ^ indicates ordered logit model; all other models are ordinary least squared (OLS) regressions. Coefficients, standard errors and p-values for each coefficient are presented in Table A1.

An alternative explanation for the generally more positive patterns at the NRC and the EPA might be that they are demographically different than the other agencies—that they have greater representation of LGBT employees, greater gender and race diversity, or their workforce is younger and thus potentially more accepting of LGBT persons than the workforce at NASA, NSF, DOE and DOT. Appendix A Table A1 provides employee demographics broken down by agency. The NRC is not an outlier in its demographic diversity nor the average age of its employees. The EPA has the highest proportion of LGBT employees (5 percent), which may help improve the experiences of LGBT persons overall in that agency [32], but has comparatively low representations of women and people of color and employees of similar average age. As such, the demographic contours of NRC and EPA do not appear to be the driving factor in the patterns documented in Figure 2.

Beyond agency differences, we hypothesized that supervisory status may insulate LGBT persons from some of the disadvantages that those lower in the organizational hierarchy encounter (H3). Table 4 presents the coefficients, p-values, and significance of the interaction term between LGBT*supervisory status. Contrary to our hypothesis, we find that none of the interaction terms are significant and all are substantively small. This suggests that the workplace experience inequalities that LGBT employees face in these agencies are not lessened among those who have obtained supervisory status. In contrast,

[8] Because the sample of LGBT respondents at NSF is numerically small (N = 28), there may be LGBT*NSF effects that are too small to be picked up by the analysis. However, the p-values on the majority of the NSF*LGBT interaction terms are quite large, lending confidence that NSF does not, indeed, provide better workplace experiences than other agencies. The sample of LGBT respondents at NRC is similarly small. Several of the NRC*LGBT interaction terms approach full or marginal significance; with a larger sample, we may see an even more substantial NRC effect.

the main effect for the supervisor indicator, which now represents results from non-LGBT supervisors, is strong and positive for most workplace experience measures, suggesting that non-LGBT persons have generally more positive workplace experiences when they are supervisors. The same does not hold for LGBT employees.

Table 4. OLS and Ordered Logistic Regression Models Predicting Workplace Experience Measures with LGBT X Supervisor Status Interaction Term (N = 37,219).

	Supervisor Coefficient	LGBT Coefficient	Supervisor * LGBT Coefficient	Supervisor * LGBT *p*-Value
Treatment as Employee Models				
Success fostered	0.203 ***	−0.115 *	0.004	0.957
Transparent evaluations	0.131 ***	−0.079	−0.041	0.572
Adequate resources	−0.049 ***	−0.169 **	0.046	0.574
Respected by supervisor	0.152 ***	−0.077	0.024	0.717
Diversity supported	0.215 ***	−0.151 *	0.026	0.768
Work Satisfaction Models				
Personal satisfaction	0.097 ***	−0.051 †	0.020	0.670
Working conditions	0.128 ***	−0.079	−0.011	0.863
Employee empowerment	0.272 ***	−0.120 *	0.041	0.580
Procedure satisfaction	0.242 ***	−0.142 *	0.018	0.823
Job satisfaction ^	0.506 ***	−0.376 *	−0.026	0.923

Note: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test). ^ indicates ordered logit model; all other models are OLS regressions.

Next, we hypothesized that, consistent with substantial cultural and legislative shifts toward LGBT equality and inclusion, younger LGBT employees would report more positive workplace experiences than their older LGBT colleagues (H4). However, there is little indication of age cohort effects: all but one of the interaction terms between LGBT status and age cohort are non-significant (Table 5).[9] We discuss the implications of these results in the next section.

Finally, we tested whether there are gender differences in the manifestation of LGBT inequality. Table 6 presents LGBT coefficients for models ran separately for men and women. We find similar patterns across both sets of models. This is confirmed by supplemental analyses (not shown) replicating the models in Table 3 with LGBT*woman interaction terms; none of the interaction terms were significant. This runs counter to possible expectations that LGBT-identifying women may experience less workplace experience disadvantages than non-LGBT women because of the cultural assumptions that non-heterosexual and transgender women are more masculine than heterosexual women. It indicates that both men and women who identify as LGBT face similar workplace experience disadvantages.[10]

9 Older LGBT workers report marginally lower satisfaction with their pay than younger LGBT workers, possibly reflecting actual wage gaps for older LGBT employees that have accumulated over time.

10 The effects for employee satisfaction and job satisfaction are negative but do not reach statistical significance for women. However, the interaction term between LGBT *gender in supplemental analysis is nonsignificant, suggesting that LGBT-identifying women and men experience similar disadvantages on those measures.

Table 5. OLS and Ordered Logistic Regression Models Predicting Workplace Experience Measures with LGBT X Age Cohort Interaction Term (N = 37,219).

	Age Cohort Coefficient	LGBT Coefficient	Age Cohort * LGBT Coefficient	Age Cohort * LGBT *p*-Value
Treatment as Employee Models				
Success fostered	0.014 †	−0.155	0.021	0.672
Transparent evaluations	0.010	−0.052	−0.013	0.788
Adequate resources	0.006	−0.247 †	0.042	0.413
Respected by supervisor	−0.004	−0.072	0.001	0.989
Diversity supported	0.001	−0.284	0.067	0.366
Work Satisfaction Models				
Personal satisfaction	0.014 **	−0.030	−0.009	0.705
Working conditions	0.026 ***	−0.133	0.026	0.574
Employee empowerment	0.039 ***	−0.116	0.004	0.978
Procedure satisfaction	0.030 ***	−0.149	0.006	0.915
Job satisfaction ^	0.067 *	−0.376	−0.001	0.998

Note: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test). ^ indicates logit model; all other models are OLS regressions.

Table 6. OLS and Ordered Logistic Regression Models Predicting Workplace Experience Measures with LGBT Status, Run separately for Women and Men.

	MEN (N = 22,550)		WOMEN (N = 14,669)	
	LGBT Coefficient	Std. Error	LGBT Coefficient	Std. Error
Treatment as Employee Models				
Success fostered	−0.119 †	0.063	−0.099 †	0.051
Transparent evaluations	−0.066	0.055	−0.112 †	0.060
Adequate resources	−0.153 **	0.055	−0.177 **	0.069
Respected by supervisor	−0.061	0.044	−0.092	0.094
Diversity supported	−0.106 †	0.053	−0.216 †	0.127
Work Satisfaction Models				
Personal satisfaction	−0.049 †	0.027	−0.045	0.073
Working conditions	−0.079	0.063	−0.087	0.112
Employee empowerment	−0.100 *	0.049	−0.136	0.086
Procedure satisfaction	−0.145 *	0.069	−0.130 **	0.046
Job satisfaction ^	−0.456 *	0.196	−0.210	0.216

Note: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test). ^ indicates ordered logit model; all other models are OLS regressions.

5. Discussion

The goal of this paper is to examine whether there are significant workplace experience inequalities for LGBT-identifying employees within STEM-related agencies and whether those inequalities vary by agency, worker supervisory status, worker age, and gender. As hypothesized, we found evidence of widespread workplace experience inequalities for LGBT employees compared to their non-LGBT colleagues. We found these inequalities to be somewhat lessened—but not completely mitigated—in agencies with primarily regulatory missions and goals. Although we cannot say for certain that the regulatory focus of these agencies produces a selection effect that deters politically conservative employees, the results for the EPA and NRC are in line with these expectations. Supplemental analyses also helped rule out demographic diversity and average age and tenure as possible explanations.

These first two sets of results have important implications. First, LGBT workplace experience inequalities appear to be quite widespread within STEM-related agencies. We find significant differences by LGBT status on a variety of workplace experience inequalities ranging from the lower likelihood of reporting that their success is fostered and they have adequate resources, to their perception of a lack of support for diversity, to lower job satisfaction.

Additionally, our results suggest that the particular socio-political context of the organization may have consequences for the experiences of LGBT persons, even if the point of politicization (in this case, regulatory functions) is not directly connected to LGBT equality issues. As noted in the introduction, antidiscrimination policies and employee benefits are held constant across these six federal agencies. The politicization of the work of other non-governmental STEM-related organizations (e.g., defense contractors or companies that use stem cells for biomedical research) may, by the nature of their central work tasks, attract employees that tend to be more or less supportive of LGBT equality and inclusion. More research is needed to understand how particular organizational focus and goals can promote more positive or negative workplace experiences for LGBT workers.

Our analysis also produced insightful null findings. First, counter to our expectations, supervisory status does not appear to insulate LGBT employees from negative workplace experiences. LGBT supervisors do not fare better than non-supervisors on any of the workplace experience measures. While supervisory status does provide workers with more authority and power within an organization, it does not appear to protect them from colleagues' bias.

Second, we found that the youngest LGBT workers in these agencies do not have systematically more positive workplace experiences than their older LGBT colleagues. This is a striking finding, as employees in these agencies who were required to gain security clearance three decades ago would have had to remain closeted in order to keep that clearance [77]. Of course, the responses of older LGBT employees may simply reflect their more positive current workplace experiences compared to more egregious heterosexism and heteronormativity in the past, but the memories of past negative workplace experiences might color their view of their current workplace experiences, compared to younger workers who have enjoyed LGBT-inclusive non-discrimination policies and a more tolerant cultural landscape for the entirety of their (short) careers. This suggests that the resolution of these LGBT inequalities is not simply a matter of waiting for this to "get better" as younger generations of LGBT persons enter the workforce their older colleagues retire.

Third, we find that there is little difference in the reported experiences of LGBT-identifying women and men. One possible alternative explanation for the results of LGBT status in the full sample is that it is not LGBT status per se that is devalued, but *femininity* within the context of a culturally masculine organizations. In this perspective, the LGBT effects would be primarily driven by the devaluation of perceived femininity among LGBT-identifying men in STEM environments. However, our results indicate that LGBT-identifying women are similarly disadvantaged compared to non-LGBT women. This suggests that the LGBT results are rooted in status biases related to the normative expectations for "normal" or "natural" performances of gender rather than just the devaluation of femininity in a masculine space.

These analyses have several limitations worth noting. FEVS is a cross-sectional survey, so we are unable to follow workers over time as they encounter and react to their workplace experiences. Future work with longitudinal data would also be better able to discern how workers' experiences change as they move into supervisory positions. Related, although we believe that the agency-specific effects are due at least in part to differences in politicized priorities that may lead to a selection of more politically liberal workers into regulatory agencies, we cannot rule out other possible explanations. Third, as the LGBT samples at some of the agencies were quite small (especially NSF and NRC), it is possible that there may be agency effects that were not picked up by the interaction terms.

Finally, the FEVS does not have data on respondents' occupation; thus we cannot distinguish between workers who are engaged directly in STEM work and those who do other types of work (e.g., administrative or human resources) in these STEM-related agencies. It would have been particularly helpful to have occupation in order to control for possible patterns of occupational segregation in these results. Some of the workplace experience differences we see by LGBT status may be due in part to the under-representation of LGBT persons in occupations within the STEM-related organizations that have less power and prestige. This may explain part of the relationship between LGBT status and adequate resources and satisfaction with working conditions.[11] For example, if LGBT employees are less likely to be in "line" positions working as STEM professionals in these STEM-related agencies, they may, by the nature of their jobs, have less adequate resources and less satisfaction with their working conditions on average than non-LGBT persons. However, most other measures (e.g., respected by supervisor, job satisfaction) are not so closely tied to occupation. To account for as much variation by job and occupation as possible, our models controlled for supervisory status and tenure.[12] Despite these limitations, these data provide an unprecedented opportunity to examine the contours of LGBT inequality among a representative sample of workers in a number of STEM-related organizations. Because recent literature has begun to demonstrate that anti-LGBT bias can be particularly pernicious among STEM professionals, we expect that these results (which include STEM and non-STEM workers in STEM-related agencies) *underestimate* the workplace experience disadvantages LGBT-identifying STEM professionals encounter.

6. Conclusions

Overall, these results illustrate that LGBT workplace experience inequalities are pervasive within STEM-related agencies, extend across age cohorts and supervisory status, and exist for both LGBT-identifying women and men. This has several implications for STEM-related organization inside and outside the federal government. As we noted in the introduction, federal agencies have expansive non-discrimination policies and bureaucratized accountability structures that formally protect LGBT employees. Nevertheless, workplace experience inequalities for LGBT persons persist in these agencies. Although many high-profile STEM organizations in the private sector have promoted LGBT inclusion for decades, these protections are not industry-wide. As such, the inequalities we document here are likely present—if not exaggerated—in STEM-related organizations in the private sector. Additionally, previous research has illustrated that workplace satisfaction and more negative treatment can reduce worker engagement and productivity [78–80]. As such, the workplace experience inequalities documented here may actually serve to reduce the productivity and efficiency of these STEM organizations.

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11 Occupational segregation by gender likely plays a role in the results by gender as well. The sample of women includes STEM workers but also likely a larger proportion of non-STEM workers than among the sample of men. As such, these results likely underestimate biases that women working in STEM jobs in these agencies encounter.

12 We found that LGBT persons were equally as likely as their non-LGBT colleagues to have supervisory responsibilities in their agency.

LGBT inequality is an informative axis of disadvantage to consider in STEM. Not only is LGBT status an important social category in its own right, but the results here suggest that consideration of LGBT status sheds light on gender inequality as well. Our results suggest that devaluation as a result of the norms of the gender structure—not just the devaluation of femininity—reproduces inequality in STEM environments. Further research is needed to discern how sexual identity and transgender status intersect with professional and organizational cultures in STEM and how these biases interface with gender biases documented in prior scholarship. Understanding how inequality is reproduced along a variety of demographic axes is the first step toward developing policies and practices that make STEM as inclusive as possible.

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Appendix A

Table A1. Demographic Characteristics of STEM-Related Agencies (N = 37,219).

	Percent LGBT	Percent Women	Percent Racial/Ethnic Minorities	Mean, Tenure Measure	Mean, Age Cohort
NRC	2.8%	36.8%	30.5%	2.19	2.45
EPA	5.0%	54.7%	29.2%	2.47	2.47
DOE	2.7%	39.7%	22.8%	2.25	2.46
NSF	4.2%	64.5%	34.6%	2.34	2.58
NASA	2.2%	36.8%	24.3%	2.47	2.46
DOT	2.7%	32.0%	29.7%	2.29	2.56

Table A2. Unstandardized Coefficients (with Standard Errors) of LGBT X Agency Interaction Terms from OLS and Ordered Logistic Regression models Predicting Workplace Experience Measures (N = 37,219).

	EPA * LGBT Coef.	**NRC * LGBT Coef.**	**NASA * LGBT Coef.**	**NSF * LGBT Coef.**	**DOT * LGBT Coef.**	**DOE * LGBT Coef.**
	(*SE*, *p*-Value)	**(*SE*, *p*-Value)**	**(*SE*, *p*-Value)**	**(*SE*, *p*-Value)**	**(*SE*, *p*-Value)**	**(*SE*, *p*-Value)**
Treatment as Employee Models						
Success fostered	0.127 (0.089, $p = 0.155$)	0.143 † (0.084, $p = 0.090$)	0.095 (0.068, $p = 0.164$)	0.094 (0.145, $p = 0.517$)	−0.067 (0.092, $p = 0.466$)	−0.088 (0.081, $p = 0.278$)
Transparent evaluations	0.074 (0.083, $p = 0.373$)	0.178 * (0.089, $p = 0.046$)	0.048 (0.067, $p = 471$)	0.054 (0.127, $p = 0.669$)	−0.066 (0.089, $p = 0.461$)	−0.022 (0.075, $p = 0.770$)
Adequate resources	0.192 * (0.084, $p = 0.023$)	0.174 † (0.102, $p = 0.090$)	0.169 * (0.069, $p = 0.014$)	0.053 (0.154, $p = 0.730$)	−0.096 (0.091, $p = 0.295$)	−0.154 * (0.074, $p = 0.038$)
Respected by supervisor	0.059 (0.082, $p = 0.475$)	0.119 (0.078, $p = 0.127$)	0.026 (0.066, $p = 0.695$)	−0.033 (0.127, $p = 0.795$)	−0.065 (0.093, $p = 0.483$)	0.037 (0.075, $p = 0.616$)
Diversity supported	0.141 (0.101, $p = 0.161$)	0.255 ** (0.089, $p = 0.004$)	0.076 (0.095, $p = 0.369$)	0.108 (0.144, $p = 0.453$)	−0.128 (0.131, $p = 0.330$)	−0.036 (0.092, $p = 0.698$)
Work Satisfaction Models						
Personal satisfaction	0.084 (0.124, $p = 0.497$)	0.330 ** (0.119, $p = 0.006$)	0.023 (0.104, $p = 0.821$)	0.137 (0.181, $p = 0.446$)	−0.032 (0.148, $p = 0.827$)	−0.098 (0.109, $p = 0.369$)
Working conditions	0.152 * (0.068, $p = 0.026$)	0.115 † (0.066, $p = 0.081$)	0.009 (0.061, $p = 0.883$)	0.087 (0.099, $p = 0.378$)	−0.056 (0.093, $p = 0.551$)	−0.144 * (0.071, $p = 0.041$)
Employee empowerment	0.114 (0.088, $p = 0.196$)	0.143 (0.100, $p = 0.153$)	0.101 (0.070, $p = 0.151$)	0.292 * (0.131, $p = 0.025$)	−0.061 (0.093, $p = 0.514$)	−0.097 (0.081, $p = 0.233$)
Procedure satisfaction	0.174 † (0.092, $p = 0.058$)	0.170 † (0.093, $p = 0.068$)	0.076 (0.073, $p = 0.302$)	0.205 (0.128, $p = 0.109$)	−0.099 (0.103, $p = 0.333$)	−0.065 (0.081, $p = 0.420$)
Job satisfaction ^	0.074 (0.106, $p = 0.485$)	0.080 (0.116, $p = 0.492$)	0.110 (0.084, $p = 0.192$)	0.093 (0.162, $p = 0.564$)	−0.047 (0.119, $p = 0.695$)	−0.065 (0.097, $p = 0.502$)

Note: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two-tailed test). ^ indicates ordered logit model; all other models are OLS regressions.

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Article

Collaboration and Gender Equity among Academic Scientists

Joya Misra [1,*], Laurel Smith-Doerr [1], Nilanjana Dasgupta [2], Gabriela Weaver [3] and Jennifer Normanly [4]

1 Department of Sociology, University of Massachusetts, Thompson Hall, 200 Hicks Way, Amherst, MA 01003, USA; lsmithdoerr@soc.umass.edu
2 Department of Psychological and Brain Sciences, University of Massachusetts, Tobin Hall, 153 Hicks Way, Amherst, MA 01003, USA; dasgupta@psych.umass.edu
3 Institute for Teaching Excellence and Faculty Development, University of Massachusetts, Goodell Building, 140 Hicks Way, Amherst, MA 01003, USA; gweaver@umass.edu
4 Department of Biochemistry and Molecular Biology, University of Massachusetts, Lederle Graduate Tower, 710 North Pleasant Street, Amherst, MA 01003, USA; normanly@biochem.umass.edu
* Correspondence: misra@soc.umass.edu; Tel.: +1-413-545-5969

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Abstract: Universities were established as hierarchical bureaucracies that reward individual attainment in evaluating success. Yet collaboration is crucial both to 21st century science and, we argue, to advancing equity for women academic scientists. We draw from research on gender equity and on collaboration in higher education, and report on data collected on one campus. Sixteen focus group meetings were held with 85 faculty members from STEM departments, separated by faculty rank and gender (i.e., assistant professor men, full professor women). Participants were asked structured questions about the role of collaboration in research, career development, and departmental decision-making. Inductive analyses of focus group data led to the development of a theoretical model in which resources, recognition, and relationships create conditions under which collaboration is likely to produce more gender equitable outcomes for STEM faculty. Ensuring women faculty have equal access to resources is central to safeguarding their success; relationships, including mutual mentoring, inclusion and collegiality, facilitate women's careers in academia; and recognition of collaborative work bolsters women's professional advancement. We further propose that gender equity will be stronger in STEM where resources, relationships, and recognition intersect—having multiplicative rather than additive effects.

Keywords: collaboration; gender equity; academic STEM careers

1. Introduction

Collaboration is essential to 21st century academic careers, particular for those in science, technology, engineering, and mathematics (STEM) fields, where research is more likely to be carried out in teams and collaborative grants and publications are common. As Kathrin Zippel notes, "Collaborations are crucial for academic career advancement as they further the exchange of ideas, skills, and expertise" [1]. Yet, collaboration presents a paradox to universities, which historically privilege individual attainment and expertise in the evaluation of success. A mismatch exists between the growing need for collaborative approaches and institutional structures developed in an earlier era of university life. We argue that addressing this mismatch can lead to better outcomes for faculty and their institutions, especially for the participation and advancement of women in STEM, a long-standing challenge for universities.[1] Collaboration may raise particular challenges for women, while fostering collaboration may be a key way to create greater equity in university settings.

Collaboration is defined here simply but broadly as people working together to solve problems. In contrast to much previous work, our approach to collaboration expands the focus beyond collaborative research products. First, we consider how much access faculty have to resources needed for research collaboration, as well as how much recognition they receive for collaborative research. Second, we consider the relational process of career development which involves mutual mentoring within a network of faculty who share information and advise one another to advance their careers. Thus, three components of collaboration are proposed as integral to faculty success: access to resources for research collaboration, recognition given to collaborative research, and collegial collaborative engagement in career advancement.

Within *research collaboration* we focus specifically on faculty working together in STEM fields because collaborative research plays a key role in scientific discovery. Indeed, diverse groups working together are particularly effective at finding solutions to complex problems [2–4]. However, to get collaborative research off the ground, resources are necessary, such as locating possible collaborators, finding specialized but necessary equipment on-campus, sharing lab space, supplies, or personnel, and coordinating experiments across labs and fields. These much-needed resources are not accessible to all faculty members, and may reflect gender inequalities.

Independent of the mechanics of conducting collaborative research, faculty members need to receive recognition for their collaborative research in STEM fields. There is considerably ambiguity within STEM fields about how to determine whether a team member has made a substantial contribution to a project. Substantial contribution may be attributed to the first author, the last author, or the corresponding author, depending on field. However, these attributions become ambiguous if a paper led by a junior author has a senior co-author on it. In that case, readers may perceive the senior author to be the intellectual driver of the project even though the junior author is the lead. Put differently, uncertainty stems from not knowing how to weight the contributions of less senior authors and other authors whose names appear in the middle of the authorship list on a paper. The same uncertainty emerges when trying to decide how much recognition should be given to faculty members who are co-principal investigators (Co-PI), or co-investigators (Co-I) on research grants instead of the Principal Investigator (PI). These ambiguities about how to recognize individual contributions within science teams may particularly affect young investigators and women scientists to the extent that they are perceived as having less expertise and lower status.

Within *collaborative career development*, we focus on faculty mutually mentoring each other in peer relationships because career development and advancement often depends on informal acquisition of knowledge through collaborative networks with colleagues [5–7]. Collaborative career development is not a hierarchical, unidirectional traditional mentoring relationship, but one based on a relational network among faculty members, since research shows that these mutual mentoring networks are particularly effective [5,7]. While collaborative career development may be common across academic fields, it may be especially pertinent to STEM faculty who have to use their professional networks to find collaborators, specialized equipment, shared supplies, and lab space. This is where informal knowledge acquisition is critical. If collaborative career development is less accessible to women, they may be disadvantaged.

We propose that ensuring resources, recognition, and relationships for collaborative work matters for gender equity in STEM. Increasing incentives and structures that promote rather than penalize faculty working together as scholarly peers simultaneously enhances the core mission of the university, produces knowledge, and benefits women's advancement. To explore how men and women faculty

[1] We posit that addressing the mismatch between collaboration and university hierarchy will also have benefits for faculty members from underrepresented racial and ethnic groups; however this paper focuses on gendered processes exclusively, given the small numbers of URM and international faculty represented in this data.

in STEM disciplines experience and understand collaboration, and its role in academic science and engineering, we conducted a study using focus group methodology with STEM faculty from a research university as participants.

To shed light on why academic collaboration might activate gender stereotypes and differentially influence career outcomes for men and women scientists and engineers we draw on expectation states theory, which argues that status plays a central role in the maintenance of inequality [8–10]. Status beliefs, or cultural stereotypes about the worthiness and competence of particular groups, influence the enactment of social hierarchies among people. In addition to status, the social context matters as well, according to expectation states theory. In contexts that are societally assumed to be men's domains, status stereotypes about gender are particularly likely to shape evaluations of women's competence. Because STEM fields are stereotyped as men's domain, status beliefs may affect how women compared to men are evaluated, rewarded, and promoted [11]. Past research shows that status beliefs influence men and women's behavior in mixed gender settings: men tend to talk more, make more task suggestions, act more assertive, and appear more influential than women [8]. Expectation states theory suggests that if women act against status expectations, others may penalize them, for example, for asserting authority or engaging in self-promoting behavior. However, it may also be the case that if a woman holds a well-recognized high status position within a professional context (e.g., Distinguished Professor of Mechanical and Industrial Engineering), her personal high status may offset gender stereotypes from being applied to evaluate her competence.

We use expectation states theory as the theoretical framework to inform our analysis of focus group data on collaboration in STEM fields. Given that STEM contexts are widely stereotyped as male domains, this provides an opportunity to examine whether social psychological processes related to status and gender stereotypes affect the extent to which women, relative to their peers who are men, gain access to institutional resources that facilitate collaboration, receive recognition for their collaborations, or receive mentorship.

2. Existing Research on Collaboration

Researchers have used multiple approaches to study collaboration in university environments. We review research in three areas: scholarship on research collaborations; how collaboration is evaluated; and collaborations that promote faculty development (e.g., peer mentoring). While much empirical research has focused on research collaboration (especially quantitative studies of co-authorship), in a recent comprehensive review of the literature on collaboration, Bozeman and colleagues note that while we now understand research collaboration from a bibliometric standpoint, much more qualitative research is needed on the meaning of collaboration and the informal side of collaboration, including mentoring [12]. By recording the meanings of collaboration raised in focus group interviews, and by conceptualizing collaboration more broadly than simply through co-authored publications, we contribute rich contextual evidence about the nature of collaboration in academic science and engineering and the relation between collaboration and equity.

2.1. Research Collaboration

Scientific, technical, and engineering innovations and discovery are increasingly driven by team-based research collaborations [2,13] and research collaboration is a strong predictor of productivity, as measured by peer-reviewed publications [14,15]. Past research on universities has identified the importance of, and strategies for, collaboration, including multi- and interdisciplinary collaboration, collaboration across institutions, and the relationship between collaboration and productivity [1,2,13–24].

Some research identifies gender differences in research collaborations. Controlling for other factors that influence collaboration, research in Europe and the U.S. suggests that women show greater preference for collaborative and interdisciplinary research, yet may have fewer collaborators and be less integrated into international research networks [1,25–33]. Men in the U.S. hold most of the prominent leadership roles in interdisciplinary research centers [13]. When women do secure positions in university research centers with ample resources for collaborative research, their career outcomes become more comparable to that of men. In contrast, women in traditional STEM departments with fewer resources for collaborative research experience larger gender gaps in rank, career satisfaction, and research funding [34]. This evidence fits with expectation states theory which would predict that in STEM fields dominated by men, women have lower status relative to men, which makes it more difficult for them to attract collaborators or gain access to resources. Indeed men, with their more privileged status, may feel more entitled than women to access resources.

2.2. Valuing Collaboration

Even as team-based science has increased, the process of evaluating faculty for tenure and promotion continues to rely almost exclusively on assessment of individual performance, which may also yield gendered results [24,35,36]. Judging individual performance based on team science can be difficult because of the ambiguity of determining who is responsible for which aspects of collaborative research, as well as inconsistencies in how collaboration is defined [17,37,38]. One estimate is that half of all collaborations are not credited by formal recognition in co-authorship [39].

Ambiguities in how to document, report, and credit collaboration may be accentuated by implicit gender bias [40–43]. A growing body of research reveals the multiple ways in which gender stereotypes unintentionally, or implicitly, bias evaluations of men's and women's professional work inside and outside academia [8,44–47]. For example, studies that have found that subtle or implicit gender bias affect hiring decisions [46,48–55], how letters of recommendation are written [56–58], how grant proposals are reviewed [59,60], how manuscripts are peer-reviewed at scientific journals [61], and evaluations of professional women's competence and likeability [48,62,63]. In other words, gender biases that emerge in evaluations of academic scientists and engineers are consistent with lessons from stereotyping research: in decision-making contexts with incomplete or ambiguous information, evaluators unintentionally use stereotypes to "fill in the gaps" and draw inferences about individuals' competence and worthiness based on those stereotypes [64,65].

One classic ambiguous situation is where evaluators make inferences about how much of the intellectual work in a collaborative team of scientists was done by individual members of that team. Because people implicitly stereotype the ideal successful scientist or engineer as male [44,45,66], when it comes to giving credit to members of a science team in the absence of complete information, these implicit gender stereotypes subtly push evaluators to assume men on the team must have made more unique contributions than the women, absent clear markers of leadership. For similar reasons, expectation states theory would also predict that in masculine professions like STEM, evaluators often assume that men (more than women) are the intellectual leaders in the team whose contribution is critical to the team's discovery.

2.3. Collaboration in Career Development

Past research suggests that collaboration in career development, including mentoring, is key to retaining women faculty in STEM [67–69]. As Kemelgor and Etzkowitz argue, "Mentors provide an indispensable relationship necessary for every young scientist, to learn the craft, the unwritten rules, and give entrée into social networks crucial to professional growth" ([70], p. 240). Through mentoring, faculty learn important insights such as how work is structured and valued in their discipline or workplace, how to access resources necessary to conduct their research, connect with potential collaborators, teach and advise students, and engage in meaningful and recognized service. Faculty mutually mentoring each other to advance their careers is a form of collaborative career development that is important to both women and men in STEM.

While traditional faculty mentoring relationships involve senior faculty members informally advising junior colleagues, research suggests peer and mutual mentoring networks are more effective than traditional top-down dyads [5–7]. Peer relationships also last longer than traditional mentoring pairs [5]. In addition, the more mentoring relationships professionals have, the greater their professional satisfaction [71]. Institutionalizing mentoring activities helps ensure that women receive professional development and career coaching that may be overlooked by more informal models [72,73]. Increasingly, institutions are developing peer mentoring networks or mentoring committees for faculty members [7,72,74].

Expectation states theory would suggest that in the STEM context, men faculty may have access to a wider network of informal faculty mentors than their women colleagues because of their higher status in science and engineering professions. Women, particularly women of color in STEM, may be excluded from collegial interactions, isolated not only socially but also professionally [68,75,76]. Being mentored by a variety of peers can mitigate isolation that is endemic for many STEM women, and may help them develop relationships with other women both within and outside their home department even when numbers are small [68,70,75]. Moreover, finding mentors, including peers, who have had similar gendered experiences is likely to be important to ensuring women's success [68,70,72].

Situated in the context of prior research, the present study uses focus groups to examine faculty experiences of collaboration in the context of their research, and professional development. The next section describes the institutional context within which these focus groups were conducted and the methodology used in the study. Following that, we detail main findings that emerged from the focus groups.

3. The Present Study: Institutional Context and Methods

We conducted research at a large research-intensive, doctoral-granting public university in the US enrolling almost 30,000 students. This university is comparable to many other land grant universities—with women composing approximately 40% of all Department Chairs and Deans. However, among STEM departments (which includes all of the NSF funded sciences) women comprise a smaller proportion of leadership positions: approximately 35% of Department Chairs, 20% of Distinguished Professors, and 25% of full professors are women. Larger proportions of women are in mid-career and pre-tenure faculty positions: 40% of associate and assistant professors are women. While men and women appear to have similar chances of attaining tenure and promotion to associate, women achieve promotion to full professor more slowly than men. Efforts toward increasing equity and inclusion for all faculty have primarily been in the arenas of work-life policies and recruitment policies, although the university also has invested in a peer-mentoring model [7] that has been particularly effective for women and members of underrepresented minorities.

Our aim was to understand the challenges that STEM faculty identified in how they were supported and credited in their work. We invited all tenure-line STEM faculty (defined as faculty in NSF-supported fields) to attend a focus group set at a specific date and time, and organized by rank and gender. Altogether, sixteen focus groups were conducted with 72 STEM faculty participants in Spring 2015. Written feedback was gathered from 13 additional participants who could not attend. The 85 faculty who provided input along with the seven faculty facilitators make up about 15% of all full-time faculty in the NSF funded science and engineering colleges at the university. Among the full professors, department heads/chairs and other former leaders were well-represented. The majority of faculty who participated in these focus groups came from natural science departments who do experimental research in laboratories (e.g., physics, chemistry, biology, neuroscience, physical anthropology) or theoretical research (e.g., mathematics, theoretical physics); others came from engineering, and computer science. A smaller minority of faculty came from non-lab oriented social sciences (e.g., economics, sociology). Table 1 shows the comprehensive list of departments for each group of faculty interviewed by rank and gender.

Table 1. STEM Fields Represented in Focus Groups.

Rank & Gender of Focus Group	Field
Assistant Men	Biochemistry and Molecular Biology, Chemistry, Chemical Engineering, Computer Science, Electrical and Computer Engineering, Mechanical and Industrial Engineering, Political Science, Psychological and Brain Sciences
Assistant Women	Astronomy, Biology, Chemistry, Chemical Engineering, Civil and Environmental Engineering, Economics, Environmental Conservation, Geosciences, Linguistics, Mechanical and Industrial Engineering, Microbiology, Physics, Psychological and Brain Sciences, Resource Economics, Sociology
Associate Men	Biochemistry and Molecular Biology, Biology, Chemistry, Civil and Environmental Engineering, Computer Science, Economics, Electrical and Computer Engineering, Landscape Architecture and Regional Planning, Sociology
Associate Women	Anthropology, Biology, Chemistry, Ecological Conservation, Math and Statistics, Physics, Psychological and Brain Sciences, Sociology
Full Men	Astronomy, Biochemistry and Molecular Biology, Biology, Chemistry, Computer Science, Linguistics, Management, Math and Statistics, Political Science, Physics, Psychological and Brain Sciences, Sociology
Full Women	Anthropology, Biology, Chemistry, Economics, Electrical and Computer Engineering, Geosciences, Mechanical and Industrial Engineering, Landscape Architecture and Regional Planning, Physics, Political Science, Psychological and Brain Sciences, Sociology

These focus groups should not be seen as representative of all STEM faculty nor should this one university be seen as representative of all research-intensive universities. In using a qualitative method like focus groups our goal was to generate new insights about the nature of professional collaborations and not necessarily to generalize to a larger population. Focus groups provide a rich hypothesis-generating mechanism by using inductive methods to identify and develop emergent themes. As compared to surveys, focus groups allow researchers to ask more nuanced questions, and receive considerably more complex answers than are possible to include in survey measures. As compared with individual interviews, focus groups benefit from the interplay between different respondents. At times, respondents disagree with one another; at other times, they chime in with similar experiences. The conversations thus capture how people make sense of their experiences; highlight convergences and divergences in their encounters at the university; and give us important insights into our respondents' understandings of their positions as faculty members. Although focus group data are not necessarily generalizable to a larger population, quantitative research that builds on focus group findings may later test the insights developed through these qualitative methods on larger, more generalizable samples.

We attempted to avoid the potential 'groupthink' outcome of focus groups where minority voices may be silenced by organizing focus groups by rank and gender. In this way, the homogenous gender/rank groups could identify concerns faced by women and men at different ranks, including attaining tenure, time to promotion, and leadership roles [77]. Department heads and chairs were informed about the focus groups and asked to encourage their faculty to attend, but the research was faculty-based (and not institutionally required). Among the six sessions divided by gender and rank, there were at least two or three tables of 4–5 people from different departments, composing sixteen groups in all. This helped avoid faculty members feeling concerned that their comments might be heard by senior colleagues, or reported back to department leaders. Given the fairly critical comments made in the focus groups (as presented in the findings), we do not expect that the faculty who attended our focus groups were reluctant to speak.

Two members of the research team, one serving as facilitator and another as note-taker, also sat at each table. Each group started with an initial conversation aimed at understanding challenges faced by faculty within that group. A structured protocol (see Appendix A) was used in which specific questions were posed to the group and responses solicited. The structured protocol included questions about mentoring, departmental decision-making, transparency in personnel decisions, support for collaborative and interdisciplinary research, job satisfaction, and barriers to faculty work. We focused on these topics based on our reading of the existing literature on collaboration and interdisciplinarity.

The final 15 minutes brought all focus groups together when a moderator asked faculty to identify some of the key interventions that the university could design to address challenges they had identified. Detailed notes of the sessions, flipcharts where intervention ideas were recorded, and the informal conversations with faculty after the session were used for data analysis.

The larger research team was composed of three social scientists, three natural scientists and one engineer. While all members of the team did not attend every focus group session, a majority of the team was at each focus group session, which led to useful insights as we compared similarities and differences across groups. The research team members wrote up summaries of their impressions immediately after each focus group, which were discussed by the entire research team to identify main themes that emerged from all-men and all-women focus groups within each rank. For example, after holding focus groups with assistant professors who were men vs. women, our research team identified key themes that emerged from these two types of groups. The team was also attentive to whether the same themes, or the same gender differences or similarities emerged from focus groups of associate and full professors. We considered whether women and men spoke of experiencing different challenges or had different interpretations of the same challenges. We found more evidence of the latter: women and men often reported the same experiences, but interpreted the same experiences through different lenses. We identified three themes in focus group responses regarding collaborations: comments about professional resources, recognition, and relationships. These themes are used to organize the results section below.

4. Findings

4.1. Resources for Collaboration

Resources always matter to research productivity; yet in STEM fields, where collaboration is critical, challenges in accessing resources to foster collaboration can be particularly problematic. This included inadequacies in staff support to get labs started and connected and facilitate collaborative grant-writing, limited collaborative research space, lack of opportunities to meet potential collaboration partners due to physical and disciplinary boundaries, and lack of seed funding to get new collaborative research off the ground. Both men and women identified these issues to collaboration, suggesting that they have similar experiences, but women seemed particularly disadvantaged in locating resources to facilitate collaboration.

A major concern voiced by faculty members was difficulty finding basic resources such as access to staff. However, there were differences in how men and women of different ranks interpreted the problem of too little staff support for collaboration. Men of all ranks and some senior women expressed frustration about the *lack of staff* to provide logistical support for collaboration. In contrast, assistant professor women talked about the *lack of time* to do the work themselves or lack of time to identify appropriate resources to support collaborations. In keeping with expectation states theory, it appears that men and senior women, holding more privileged status, feel more entitled to resources than junior women.

Staffing was a key theme in all of our focus groups, even though we did not explicitly ask about staffing (see Appendix A). Focus group members noted how much more productive they would be, and how many more research collaborations they could develop, if they had adequate staff support, given the particularly time-consuming nature of organizing teams of collaborators. In one group of associate professor men, a faculty member argued that, while colleagues at other universities receive 20 h a week of administrative support, he receives "much closer to zero administrative support, which affects my productivity." Another associate man responded that inadequacies in staffing particularly affect interdisciplinary research collaboration: "Support makes a big difference. I recently put in [a grant] proposal with someone who had administrative help and that was great. You could focus on stuff you're good at." Faculty members also discussed the high level of administrative demands beyond research work, and how this work takes faculty time away from collaborative research and teaching activities.

With a shrinking tenure-line faculty, and increased administrative demands, faculty described frustration with doing clerical and administrative work that could be carried out by staff, rather than what they viewed to be the key elements of their jobs. This clerical work gets in the way of developing relationships with new collaborators, while also slowing progress on existing collaborations. Both men and women identify a problem in how much clerical work they do to support collaborations, but junior women tended to be more apologetic, suggesting that they understood staffing constraints meant that they had to take on more administrative work. However, senior women faculty opinions tended to align with men. For example, one woman who is an associate professor responded to our focus group questions in writing took a tone more similar to the men's comments, noting: "There is *so much* that could be done 10–20 h/week by an administrative assistant, if I had one. My life would be *dramatically* improved if I had a 10–15 h/week secretary (emphasis hers)." One group of associate women faculty members agreed that men talked about and shared resources that facilitate collaboration more, in part because they were more integrated with their colleagues. As one associate professor argued "some department members got grant prep[aration] assistance, [there should be] transparency that everyone gets the same access to staff support." Applying for funding to support collaborative research is hampered when women faculty members cannot access grant preparation support.

Assistant professor men conveyed frustration in words, tone, and body language with the lack of staff support for research collaborations. One man who is a full professor noted the challenge for new faculty, arguing that they "get the run around when trying to set up their research programs—very opaque processes." Assistant professor men described relying on seasoned colleagues (usually senior men) to advise them about the resources they needed. In contrast, assistant professor women were more likely to blame themselves for their inability to find existing resources to support collaboration. Assistant professor women described needing more information about where and how to access institutional resources. One described the time-consuming nature of getting important and necessary information—"it's not that the info doesn't exist or people aren't helpful, [but] you spend two days [looking for it]." Assistant women seemed to lack mentoring to find resources, something their men took for granted in our focus group discussions. Yet the junior women suggested that, if they were less busy, they would learn to navigate the system and develop collaborations with colleagues. Most did not consider that what was lacking was not time, so much as appropriate staffing and mentoring to identify research-related resources on-campus.

In addition, faculty voiced substantial challenges around buildings and lab space, some of which was not adequate for their work. Both men and women were concerned about space that would permit collaborative research to thrive. One woman full professor argued, "Space is not transparent; I got . . . an un-renovated lab that was supposed to be torn down. I'm the only one in the department in that building—me and retirees." An associate man similarly noted that he was "isolated" with a few other senior faculty in a different building, which limits his ability to build collaborations. As he explains, "All the new faculty go to the new building. When people visit, they say and think—'you weren't good enough to move to the new building?'" In a university where some departments are located across buildings, some faculty feel geographically isolated and this limits opportunities to collaborate with their colleagues. Space was therefore a barrier to collaborative research, especially potential collaborators were located in distant buildings.

Another concern involved scarce opportunities to meet and engage with potential collaborators. Faculty in our focus groups described how they often experienced roadblocks from units that were supposed to support collaboration. Assistant professor men noted a "huge wall" between colleges within the same university, such as the college of natural sciences and the college of engineering that made it almost impossible to engage in interdisciplinary collaboration between two colleges. Assistant women also described roadblocks to finding collaborators. One assistant woman noted that, because her department's faculty has been changing, "I don't have anyone senior that I can say 'hey, do you want to collaborate?'" She further noted that, because her research requires large computing power, she lost two years of research time because her Dean would not provide her with an adequate computer. Yet, she characterized herself as "very happy with [her] department, just issues I had to work through." While she and other assistant women had experienced obstacles that had seriously impacted their collaborative work, they downplayed these concerns. Untenured women may recognize that being assertive could lead to negative repercussions in fields dominating by men as such behavior goes against status expectations for women. This awareness may lead them to soften complaints.

Related to the concerns about finding collaborators was the need for internal seed funding to pay for research assistants, supplies, and initial pilot data to stimulate a new collaborative project and set the stage for a future collaborative grant proposal seeking external funding. For example, one assistant man argued, "[my previous university] would give small seed grants to fund interdisciplinary collaboration among faculty in different departments." At another table of assistant professor men, one argued,

> My work is very interdisciplinary. There's not much chance to interact with other departments. The exception is [interdisciplinary program with] cross-college faculty members. Faculty share what they are doing, but beyond that, is there other support? There are no seed grants for working together. This is discouraging.

STEM faculty men looked for additional resources that would allow them to develop more robust interdisciplinary collaborations. Assistant men also noted that the lack of university-supported research assistants made it difficult for them to get their collaborative research programs off the ground: "the absence of RA-ships for graduate students makes it difficult to attract graduate students without [my] already having grants." Assistant men suggested that support for interdisciplinary RAs and postdocs would be a major resource that would help facilitate collaboration across units or faculty at the university. While many of the assistant women in our focus groups came from engineering and lab science fields that emphasize collaboration, they did not make the same claims for internal funding for RAs and postdocs.

Overall, we found that faculty were concerned about the lack of resources for collaboration available at the university, despite the importance of collaboration to their careers. Assistant women tended to blame a lack of accessible information or themselves for not being able to identify resources, while assistant men were more critical of the lack of staff and resources to support their collaborative research. We also found that men were somewhat more likely to have colleagues helping them learn about how to access resources for collaboration, while women were less integrated. As a result, women seem disadvantaged in gaining access to resources needed for collaboration, even as both men and women identify this as an issue they face.

4.2. Recognition

Recognition was a second theme that emerged from our focus groups. The key recognition narrative focused on how collaboration was perceived during tenure and promotion at the university. Faculty spoke about the difficulty getting institutional recognition for collaborative and interdisciplinary research when it came time for tenure and also for promotion to full. Expectation states theory and implicit bias research suggests that in male-dominated contexts where gender stereotypes favor men, women may get less credit for collaborative research than men in personnel actions like tenure and promotion—if the independent contributions of individual team members is not self-evident in co-authored publications and grants.

The challenges of evaluating collaborative and interdisciplinary research in personnel actions was a topic that came up among both men and women faculty. Because funding agencies tend to prioritize collaborative work, many STEM faculty carry out collaborative and interdisciplinary projects. Yet, they noted personnel evaluation gave primacy to independent research without collaborators. Both men and women saw a need for personnel committees to have greater training in evaluating collaborative research during personnel actions. Funding and personnel evaluation seemed at odds to many of our respondents. In one interchange, assistant professor men described the challenges of doing collaborative research in the current funding environment, where funding is harder to get, and there is a greater support for collaborative research than for individual principal investigators (PIs):

> Assistant Man 1: The old standard used to be that you have to get a grant and be the PI on it. Now it's more common to be a co-PI (instead of PI) or get a collaborative grant.
>
> Assistant Man 2: Collaborative work often raises questions in people's mind about who the "real" leader is in a collaborative project.
>
> Assistant Man 1: In my department, collaborative work would not count as my work. This is made very explicit in my department.

A woman assistant professor made a similar argument in another focus group:

> It's not olden days for funding. Everyone is trying to be in a silo to write grants, and [they are] not going to get funded. Interdisciplinary efforts get funded ... saying you won't get promoted if [you are] co-investigator or co-PI on the grant ... is throwing the baby out with bathwater.

Another assistant woman similarly noted, "I feel like [the university] is shooting itself in the foot with that. If collaborative grants were valued and you could still show your independent contributions, it would cost the university a lot less money in terms of start-ups and having to hire people." Devaluing collaborative grants left these faculty feeling uncertain about how to carry out their research programs, given tensions between collaborative funding opportunities but emphasis on individual grant-getting at the university.

These issues are also challenges for interdisciplinary scholars. One assistant professor man argued regarding his department, "People have had shaky tenure cases before because they've been doing interdisciplinary research." A woman assistant professor noted that she had received "mixed messages" about interdisciplinary research: "There is a difference between valued and useful for your tenure package. Interdisciplinary is awesome and cool, but you will have plenty of time to do this later." As one full man noted, comments from interdisciplinary program directors are "never used" in personnel decisions, even though they should be according to personnel procedures. Another full man noted that "the places where it has failed is where [a] junior faculty does interdisciplinary research that the department doesn't buy into."

One woman assistant said that even with interdisciplinary hires, "the department wants them to work on one discipline especially when comes to evaluation of performance. If you brought [a] grant as a co-PI, and if you are on many, many papers, but you are not the first author, it is discounted." A woman associate professor argued,

> It would almost be politically incorrect to say we do not support interdisciplinary research. I think we are open verbally ... the [research] literature they are bringing in [to their paper] is [interdisciplinary], but the co-authorships are not. Again, coming back to the cultural impediments, high impact journals are the ones that are very field and disciplinary specific, no matter how interdisciplinary, that is where you are going to get published and read, not in interdisciplinary venues. There is a conflict there.

A full professor who is a woman similarly argued that "disciplinary flagship journals are valued more than interdisciplinary journals," leading to a conversation about how external letter writers might review interdisciplinary faculty poorly who are up for tenure and promotion if judging simply by the standards of their field. We also heard from a woman associate professor who felt that since external reviewers are usually within the field, "if someone has a big interdisciplinary focus," it would be challenging to find external reviewers who do not judge them primarily on "what they are doing for the field." This suggests that doing interdisciplinary research is not entirely recognized in tenure and promotion decision.

Both men and women noted that there are increased pressures to collaborate, particularly for external funding, but that recognition for collaborative work is more problematic, including difficulty in proving leadership in collaborations. One major concern for those evaluating personnel cases is determining how central a faculty member's work is to a particular collaboration. In one conversation among full professor men, one faculty member noted that evaluation depends on whether the research is "thematically related or are they just doing a task for six different labs—how involved are they in the collaborative work?" Another full professor who is a man noted that judging credit for "collaborative projects requires significant contribution—work with people who are different enough so that your contribution is clear." Many faculty similarly called for identifying exactly what the faculty member's contribution is in a collaboration. In a conversation with full women, one noted "academia emphasizes what *you* did in evaluations. The PI for example is rewarded; the co-PI is not" on collaborative projects. Yet a full professor man noted that, in the best collaborations, clear delineations of contributions "are hard to define because there has been so much interaction."

Although both men and women raised the issue of how to credit collaborative work, women faculty were more likely to report substantial concerns about lack of recognition for their collaborative work. One full professor woman suggested that, although it is "sold as a positive in recruiting ... [tenure and promotion] discussions are very negative about collaborations, with even first authorship downgraded." An associate woman professor similarly noted, "If you collaborate, it's not independent work, so it's basically ignored." One assistant woman professor argued regarding her collaborative work, "I don't know what I need to do to demonstrate that I've been part of the team, bringing something to the table, rather than riding on others' coattails." Another woman assistant professor argued that

> the advice I got was to work on my own work. They don't really count much of these collaborative papers unless it's your students, your name. If you're the co-PI on a collaborative grant, the money is kind of discounted, especially related to tenure and promotion.

This is very challenging for faculty members trying to ensure both research funding and promotion.

One conversation provides a glimpse into how full professor women understood collaborative research, and how they assessed their colleagues, as well as themselves. One woman who is a full professor noted, "Without collaboration, I would not have lots of NIH money, but I would not have dared before full promotion. It's not so valued in my department, crossing the line so far as [discipline] goes, and [it] would not have been seen as a good thing before full professorship." Another full woman argued, regarding engaging in collaborative research, "not before tenure, I tell juniors to stay within line" while another said "even then, not until they are a full professor." Women at this table further noted that engaging in interdisciplinary research was perceived as "crossing into uncharted territory," and that while it could bring "notoriety for junior faculty," they "want people to take a safer path." While both men and women reflected that receiving recognition for collaborative work was challenging, women were much more likely to bring up this topic, and spent much more time discussing these problems.

Men appeared less likely to recount problems in how their own collaborative research was considered in their evaluations. For example, one associate man noted, "I had several research projects and worked with people outside the department. That was important for my work. I never thought of how this was viewed by my department." In answer to a question as to whether he did this collaborative research pre-tenure, he further noted "Not an issue. It worked well in terms of work and publications. Equal work from all PIs." However, another associate man suggested, "If you don't have publications by yourself it is bad/viewed negatively. If you have your own publications and some with others—it is good. If all of your research is collaborative—you are not capable of doing your own research." This man suggests that collaborative research is read within the context of a broader research agenda, and at least some solo publications are necessary (although this norm likely varies by field). Overall, it is interesting that women at all ranks were more likely to emphasize the challenge of assigning credit for collaborative research, while fewer men emphasized it as a central problem.

To summarize, we found that faculty raised a number of issues around recognition, including of their collaborative research. Both men and women identified challenges in receiving recognition for collaborative and interdisciplinary research, but women seem to express more concern about receiving recognition for collaborative research than men faculty. This finding fits with expectation states theory, which suggests that women may, in fact, get less credit than men peers if they are in fields where women as a group are stereotyped as being less competent relative to men. Given the importance of collaboration to STEM research, experiences of engaging in collaborative research without receiving adequate credit further limits women's advancement.

4.3. Relationships

Career development through peer mentoring collaborations was another critical point of conversation. One of the key themes that emerged was the type of mentoring structures that were effective or ineffective for faculty, such as formal versus informal mentoring, or top-down versus peer mentoring. Faculty also discussed mentoring support on papers and grant applications, and concerns around how to receive effective mentoring about getting grants given the current scarcity of funding. A final theme focused on concerns about burdening mentors or feeling burdened by mentoring. Men and women both discussed these issues, though men were more likely to report sustained mentoring from a range of colleagues, while women were more likely to report concerns about burdening mentors. Expectation states theory helps explain why men may be more likely to be mentored in male-dominated fields, as their colleagues may be more likely to see them as competent, and thus worthy of mentoring. Women's concerns about burdening their mentors may reflect their attempts to live up to status expectations of women to care for others and think communally.

Many of the faculty were aware of the importance of professional development and faculty mentoring. This awareness meant that more departments assigned mentors to faculty when they joined the university. Yet, these assigned mentoring relationships were not altogether successful. Most men and women noted that assigned mentors were seldom activated. One assistant woman professor said her assigned mentors "rarely met with me and were not particularly helpful." An associate woman described her department as "dominated by older white men," and said "I don't know if I was assigned a mentor, but my mentoring came from my graduate student friends and colleagues." One associate man noted that assigned mentoring worked only "so-so," arguing that it "depended on whether personalities matched up." As one assistant woman, 18 months into her time at the university reflected, "I have my mentoring committee, but I haven't really talked with them ... but I'm going to do it soon." Here again, we noted that women tended to blame themselves for the challenges that they face. Rather than wondering why her "mentoring team" had not contacted her, she expressed guilt for not contacting them.

While hierarchically assigned mentoring was not altogether successful, peer mentors were more helpful. The most successful formal mentoring programs involved peer mentoring networks that operated at department or college level, rather than a hierarchical relationship between a senior mentor with a junior mentee. For example, an assistant woman described a mentoring group in her college:

> We felt a little frustrated in our department, and we had no senior women faculty at the time, so we did a College ... mentoring group for women that focused on issues of research, teaching, work-life balance. Women of all ranks were included.

Here, junior women have created a peer mentoring program to provide each other with support that had been missing within their department. Another group of associate women discussed a previous mentoring program funded by an external grant that was no longer active because the funding had ended:

> we all shared a love of the mentoring program we had pre-tenure and . . . that is lacking, post-tenure . . . it was so productive, we would all like to see an effort, built in structurally. It needs to be institutionalized, can't be just depending on funding, gone away the next year.

One full professor who is a man also argued for this sort of mentoring system, adding that multiple types of mentoring are important—not just one (powerful) mentor. One larger department runs faculty mentoring sessions every other year for new faculty. These sessions count as departmental service for the senior faculty member running the sessions. An assistant man described the sessions: "[We have] monthly mentoring session for junior faculty around special topics (applying for NSF CAREER awards, balancing teaching and research, etc.) . . . We discuss teaching, balancing research, getting tenure, like 5–6 sessions a year." Other faculty around the table thought this was an excellent idea, given that the advice is tailored to the needs of junior faculty members in that department. In all of these examples, cross-rank mutual mentoring networks institutionalized within departments or colleges, as opposed to individual assigned mentors, seemed to receive enthusiastic support.

One of the issues raised by faculty was whether there was a culture of mentoring in departments. For example, one associate man noted that he had lunch with his assigned mentor once a month, who served as his "official point person," while those in his research area "are fairly close, so [they provide] lots of mentoring for things—grant writing to teaching." Yet, he further noted "That's the culture of my group. It's not true for all groups in the department." An associate woman also noted, "I've not experienced any mentoring as an associate prof. There is no structure [for it]. There are people who would be willing, they're not hostile. It's just not part of the culture." An assistant woman conveyed that her assigned mentor did not work out and there is "no culture of mentoring" in her department. Interestingly, this missing "culture" of mentoring seemed most evident to women. However, one associate man expressed similar sentiments about mid-career faculty: while "mentoring for junior [faculty] is good. Once you get tenure, that system collapses."

In addition to formal mentoring programs, faculty respondents also discussed informal mentoring. Men argued that they received a great deal of informal mentoring, making the formal mentoring less important. Comments among the assistant and associate men in different sessions and tables were fairly consistent:

> Assistant man: The lunch bunch [including faculty of all ranks] discusses what is "valued" within the department. Learning this is important and one can only learn it by talking to people. You have to get some sense of what's valued and not, what should you focus on with limited time. I got this in the informal discussions, because no one will actually tell you: How many students? How many papers? No one will tell you in the formal conversations.

> Assistant man: There are five or six people giving me comments so I get as much as I want or more. There are monthly lunches with mentors, and I stop by [their offices] when I have questions.

> Associate man: Informal mentoring may focus on grant writing, teaching, and identifying collaborators. Where mentoring does not exist formally, faculty still form collegial relationships and aim to help junior faculty succeed.

> Associate man: There were many [faculty] interested in my success when I arrived. People read my grants, helped me formulate lectures, get matched up with people.

All in all, most assistant and associate men expressed that they were collaborating with their colleagues to enhance career development very effectively.

Women tended to feel less engaged with informal mentoring, particularly when they were in departments made up mostly of men. An assistant woman argued, "Networking depends on being part of the boys' club, and women can't do that," noting that much socializing occurs after 5 pm, which is difficult for mothers, even though many men are also fathers. An associate woman similarly referred to informal mentoring as "the men chumming around [after] work." One woman who is a full professor argued, "Male mentoring happens organically, on the golf course, but women keep busy, but don't hang out outside of getting things done." For many of the women, this sort of informal collaborative work toward professional development seemed out of reach.

Men full professors, many of whom noted that they had not experienced formal mentoring themselves, were less certain about the need for institutionalized mentoring. Women full professors were somewhat more divided about mentoring. A number of full professor women noted that there was "no mentoring after tenure" or that "mentoring is only for junior faculty," calling for more peer mentoring efforts aimed at senior faculty. Yet in one group of women full professors, one referred to peer mentoring as "fabulous," while another suggested that formal and institutionalized mentoring was "intrusive and infantilizing." Similarly, in one discussion of why faculty were slow to advance to full in one department, full professor men suggested that those faculty were "too cautious," while one noted that "we found our own way, there is too much spoon feeding [now]."

Some men who are full professors suggested that processes such as departmental seminars, where faculty might present their work, or regular pre-tenure personnel evaluations, provided the necessary mentoring, and were skeptical about the need for additional mentoring efforts. One full professor who is a man said, "[We] have an informal system and talk about making it more formal, but it seems to work well. When it breaks down, the department head steps in. We also have—with one gap [one case where the junior faculty did not get mentored]—the department head and head of the personnel committee meet with junior faculty early in fall and talk about generalities—expectations, and meet informally." In this discussion, there appeared to be a disconnect between the mentoring that associate and assistant professors wished for and the mentoring that some full professor men thought was appropriate.

Respondents also discussed the mentoring that they received on papers and grants, suggesting that it was easier to ask for specific feedback. One assistant professor woman noted about her formal mentors:

> I do get [feedback], if I bug them, like [on] a grant, I ask them to read my grant ... but they are both senior people. I don't feel that connection, maybe [I have questions about] very stupid things about student, [they'll say] 'learn to deal with it,' no real suggestions. There is no real understanding between my situation and their situation."

Some assistant and associate women suggested that men mentors were more likely to collaborate with men mentees, and read their proposals and paper drafts, but were less focused on mentoring women. As one assistant woman noted, "overall, I'd characterize the mentoring environment in the department as one of benign neglect." One associate woman argued that men were more likely to mentor other men, "It's the case that men will talk to junior women, but won't read a paper ... That's the male style of mentoring and it's rare to do any at all." From her standpoint, men were less likely to read and provide feedback to women. This may because their senior colleagues are implicitly less likely to view women as worthy of this mentoring help. Men did not report these types of experiences.

Women respondents were particularly likely to point to mentoring as a burden. Women expressed concern about taking time from their mentor's busy schedules, but we did not hear this theme among men. One assistant woman wistfully described that she did not take full advantage of her mentors in her first year: "I had wonderful mentors, and they have advanced to other positions ... and have new mentees in their first year, but you didn't know all the questions to ask yet." Assistant women in different focus groups tended to make the same points about not wanting to burden their mentors:

> Assistant woman: I find that often it's the stuff I don't know to ask about that ends up being an issue...[but] I really don't want to take up more of my mentor's time than I already do.
>
> Assistant woman: As a junior faculty, you don't want to bother people.

> Assistant woman: You feel like everyone is so busy, you don't feel like always going to someone's office, would be nice to have senior faculty to initiate it."

> Assistant woman: You do sometimes feel like you do not know if your issue is big enough to bug them.

However, one woman in her first year as an assistant professor noted that she was "always asking questions," and felt that being proactive was working well for her.

Our respondents suggest mentoring tended to go unrecognized and unrewarded. One assistant woman suggested, "Mentoring should be initiated by senior faculty and include [mentoring regarding] amount and types of service to undertake and grant writing. Maybe senior faculty should get service credit for mentoring—[the university should] incentivize it." From her standpoint, by creating incentives to mentor, faculty would be more likely to engage in needed mentoring. Another assistant woman argued, "[mentoring is] almost out of the goodness of the faculty hearts. The people that genuinely care, but if mentoring is that critical, then mentors should get credit somehow at some level." One associate woman noted that though she is now a mentor, she has no time, suggesting that course releases would facilitate tenured faculty serving as mentors. While many women full professors valued interactions with other women at the same level, they also felt overwhelmed by work demands, including mentoring. Some full professor women called for more information resources to be put online, so that they could direct junior faculty to the resources they need to do their jobs well to make mentoring less time-consuming. Women untenured faculty further mentioned the lack of incentives to mentor, despite their need for mentoring. Faculty suggested personnel committees need to do more to value the mentoring and service work that facilitates a collaborative climate.

The key concern assistant professor men mentioned was about the changing funding environment, especially with respect to both the increasing scarcity of federal grants and greater emphasis on collaborative research. As one assistant man argued:

> Funding is tight these days. It's sometimes hard to get mentoring around grants because senior faculty without funding may not have gotten a grant in this climate. Now people are scrambling to find a way to sustain funding in a new environment, people who before had these massive labs, just don't.

Women also expressed these concerns, such as the assistant woman who said, "I have to say it's harder with the funding situation. Before juniors could get funding in first or second round, money to solve research questions, but now the funding is a problem and still on top of that, we're junior faculty." Both men and women reflected that they may not receive effective grants mentoring if older colleagues have not had similar experiences.

Overall, when it comes to collaboration in career development, we heard more differences in the experiences of men and women, although they both agree about the need for mentoring, especially around grant proposals. While assistant and associate men could recount substantial mentoring engagement, much of it informal, assistant and associate women reported less mentoring. Women provided examples of the difficulty of connecting with colleagues, and receiving feedback on their work more than men. Women also were concerned about the time-consuming nature of mentoring, and the lack of incentives to mentor faculty colleagues—making them more cautious about requesting time and attention from their mentors.

5. Conclusions

For most STEM faculty, research collaboration is crucial for research productivity and career advancement. Yet, there may be gender differences in the resources available for research collaboration and how contributions to collaborations are evaluated. At the same time, while collaboration in career development is also important to developing social networks and teach faculty members the informal norms that lead to career success, women in STEM fields dominated by men may be less likely to be engaged in these collaborations. Based on focus group data from STEM faculty at one research university, we find that faculty primarily identified three major issues around collaboration: *resources* for research collaboration, *recognition* for collaborative work, and collaborative *relationships* that support professional development, as illustrated in Figure 1. These three themes reflect many of the issues raised in the literature we reviewed on research collaboration and collaborative professional development, but also may serve as a broader framework to address gender equity in the academy [68,73,78–80].

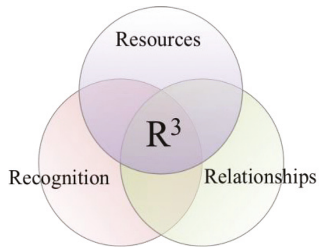

Figure 1. Interactive Model of Resources, Recognition, and Relationships.

By holding our focus groups separately by gender and rank, we were able to identify both similarities and differences in how men and women, at different ranks, perceive the climate for collaboration at their university. While all faculty noted the need for greater resources for collaboration, men expressed greater outward frustration about the lack of resources, and women were more likely to identify their own inability to access resources needed for collaboration. Women were also much more concerned about how their collaborative research was viewed. Indeed, even senior women thought that they would not be credited as making contributions to their collaborative research. While both men and women expressed that formal assigned mentoring was not particularly effective, men were much more likely to describe informal mentoring that they received that was invaluable to their career development. In comparison, women were less likely to report these types of supports, and worried about asking for their mentors' time, which led them to feel less certain about whether they were making good career decisions.

Despite being located at a university that has developed supports for STEM women, it appears that men and women continue to experience their work quite differently. In keeping with expectation states theory women's and men's different statuses in STEM fields may have affected their experiences. If a particular field is framed as masculine, status beliefs about women may be based on the implicit stereotypes that women have less expertise in that field. Those who hold more privileged statuses—such as men and, in some cases, senior women, feel more entitled to resources and mentoring than junior women. In comparison, those who hold less privileged statuses, such as assistant and associate women, express substantial concern that they are less likely to be credited in their collaborative research. Men also appear to benefit from more consistent mentorship from colleagues whereas women express concerns about burdening mentors, which may reflect their attempts to live up to communal status expectations for women.

Expectation states theory does not suggest that these statuses are fixed. Even if women are viewed as less competent, other statuses, such as being a full professor, can counteract the status effects of gender. Indeed, senior women were more likely to make strong claims about needing resources for collaboration that mimicked men's. In other words, gender differences in faculty responses were more apparent among untenured men and women than full professors. It is important to recognize the gendered experiences and understandings of untenured faculty because it may lead to differential rates of tenure, promotion, and professional success. If untenured women make fewer claims for resources, are less likely to be recognized for their contributions for collaborations, and are less likely to be engaged in collaborative career development—they may also be less likely to attain tenure and promotion. This pattern then reinforces assumptions that women may be less competent in particular fields.

These findings also provide insights into the factors that could lead to greater gender equity. Although our framing was around collaboration, our findings suggest that women's professional outcomes may be better in units where they have access to the same resources, recognition, and professional relationships as men. Substantial research has pointed to how women may not be able to access the same resources as men [43,68,73,78,81–87]; for example women may receive less investment through research funds, which limits their research productivity. The existing literature also points to the crucial role that relationships play in academic workplaces [6,7,67,74,88–94]. If men are more readily integrated into faculty networks, they may find it easier to learn the informal workplace norms and access information that helps them succeed. Research also suggests that recognition via transparent evaluation processes and communication matters, particularly regarding women's advancement [15,80,86,95–99].

We suggest that each of these factors—resources, recognition, and relationships—matter to academic success for STEM faculty. Moreover, our data suggests that when resources, relationships, and recognition intersect—as when a faculty member knows how to access essential resources (staff, space), whom to ask for help (a mentor or a staff member), and how his or her activities will be evaluated (as in the departmental personnel committee)—the effects are multiplicative rather than additive (see Figure 1). In other words, where access to all three "R"s exists (the central portion of Figure 1), the professional conditions are optimal, and we expect to see greater gender equity in retention, job satisfaction, and advancement of women STEM faculty. The area where two Rs intersect will lead to better outcomes than in the areas where only resources or recognition or relationships support collaboration. These factors influence each other in a bi-directional manner. Resources catalyze relationships and recognition. Recognition creates opportunities to attract more resources and build new relationships. Relationships help connect faculty to resources and receive greater recognition. All three factors matter, and indeed, the accounts from our focus group suggest that relationships are truly crucial for faculty to learn how to access resources and gain recognition or their collaborative work. We suggest that this model may be useful to universities as they address the challenges of gender equity. By examining and ensuring gender equity in resources, relationships, and recognition, in a variety of domains, it should be possible to develop strong and effective supports for women in STEM fields.

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Appendix A.

The interviews began with an introduction that provided broad context for the discussion, and our goals, followed by focus group discussions at separate tables regarding the following questions.

Q1. What support for peer mentoring exists (if any) in your department?

Q2. How are decisions made in your department—do you think decisions are made hierarchically, or more collectively? (for example, do chairs consult and make decisions, do committees decide/how are committees selected)

Q2B. Relatedly, how much transparency would you say exists around personnel decisions in your department? (promotion, tenure, merit, distinguished, teaching awards)

Q3. In your own work, do you engage in interdisciplinary research?

Q3A. Do you see interdisciplinary research as supported by your department? (i.e., How do you think interdisciplinary research will come into play when it comes time for tenure review?)

Q4. What do you think the general level of satisfaction is among faculty in your department? (why?)

Q5. What barriers do you perceive to faculty work?

After these small group discussion were completed (after about 40 minutes), we shifted to a large group discussion, for all of the participants in the room. We first provided data on the race, gender, and rank breakdown of faculty in STEM fields. We also presented results of a survey that indicated that men perceive more equal treatment than women in personnel decisions, and asked the participants to discuss the data.

Q6. Are these data surprising? Why do you think there is a gender gap?

Q7. What recommendations do you have for interventions to address perceived barriers to faculty work?

Q7A. Are there ways that decision-making could be improved?

Q7B. Would you recommend additional support for interdisciplinary research, and if so how?

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