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About the Editor

Joachim Wagner

Prof. Dr. Joachim Wagner (*1954) studied Economics at the University of Hannover (Germany), where he received his diploma in 1979, his doctoral degree in 1984, and his habilitation in 1990. Since 1993, he has been a Professor of Economics at Leuphana University Lüneburg (Germany). His main areas of research are international firm activities and applied microeconometrics. He has published more than 200 papers in international journals. He is an editor of the Journal of Economics and Statistics and a co-editor of Economies. Joachim Wagner is research professor at the Kiel Institute for the World Economy.

Preface

In recent years, we have all faced many new and challenging economic problems (including the financial crisis, the COVID pandemic, energy shortages due to the war in Ukraine, and a comeback of inflation). Economists contribute to the analysis of these and many other problems by using elaborate econometric methods and newly available data, often collected at the micro level of economic agents (firms and households). This Special Issue of Economies collects applied economic papers with a focus on Germany, one of the leading economies in Europe. The research areas covered include the following: the labour market (firms' use of temporary employment; the use of a large-scale short-time work scheme during the pandemic); entrepreneurship (youth entrepreneurship in Germany); industrial relations (union wage premium in Germany); innovation (regional inventor networks); digitalization (online channel sales premiums in times of COVID-19; data protection, cookie consent, and prices); international firm activities (website premiums for extensive margins of international firm activities); among others. The results reported in these papers can help to understand contemporary challenges and inform policy makers to find solutions to some pressing problems.

Joachim Wagner
Editor

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Article

Invention in Times of Global Challenges: A Text-Based Study of Remote Sensing and Global Public Goods

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Abstract: We study whether remote sensing (RS), a set of technologies with global reach and a variety of applications, can be considered instrumental to the provision of global public goods (GPG). We exploit text information from patent data and apply structural topic modeling to identify topics related (or relevant) to GPG provision, and trace their participation in the evolution of remote sensing technology over time. We develop a new indicator of affinity to GPG (and other themes) using meta information from our dataset. We find that, first, RS displays features of a general-purpose technology. Second, while peripheral, GPG-relevant topics are present in the RS topic space, and in some cases overlap with topics with high affinity in AI and participation of public sector actors in invention. With our analysis, we contribute to a better understanding of the interplay between the dynamics of technology and (global) political economy, a field of research yet under-explored.

Keywords: remote sensing; global public goods; patents; unsupervised ML; structural topic modeling; text as data

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1. Introduction

It is not the first time in the history of humanity that societies are riddled with tensions and profound transformations. The very globalization of trade emerged at regular intervals throughout modern history (Arrighi 1994). However, the global scale of challenges that humankind faces nowadays is an absolute novelty: we are navigating a 'polycrisis' landscape, while, at the same time, being enveloped in a techno-economic paradigm shaped by information and communication technologies (Lombardi and Vannuccini 2022). The polycrisis we face is the convergence of several interconnected global challenges, ranging from climate change to (geo)political and economic vulnerabilities. The solution of such challenges requires global coordination amongst actors of different types (international institutions, nations, and transnational organizations), aimed at the provision of global public goods (GPG) and dealing with global commons. As classic public goods, GPGs are non-excludable and non-rival; however, they affect population at the world scale. While the coordination failures emerging when contributing to GPGs are relatively well studied (Buchholz and Sandler 2021), we know much less about how technology might facilitate the provision of GPGs. In other words, can a given technology be instrumental to the provision of GPG? In this paper, we explore a specific set of technologies—remote sensing (RS)—whose uses are multi-scale in nature and potentially directed at areas connected with public good provision.

RS technology is a type of data or information acquisition technology (Savona et al. 2022). It can be defined as "the acquisition of information about an object or phenomenon without making physical contact with the object, in contrast to in situ or on–site observation".[1] In brief, the activity of RS employs sensor technology for detection at a distance. The global scope of RS applications makes it an interesting case to study the interplay of technology dynamics and GPGs. Furthermore, the tremendous cost decline of sensors during the last two decades together with miniaturization have strongly fostered the diffusion of the technology across a wide array of domains, making RS a good candidate to be a general purpose technology (GPT).

Given its features and applications, we hypothesize that RS can play an instrumental role in the provision of GPGs. In fact, some of the technical challenges related to GPGs are strongly dependent on information acquisition from a distance. For example, protecting ecosystems, preserving biodiversity, monitoring climate change, addressing flows of refugees, or identifying terrorist threats, just to name a few, are activities that rely (or might rely) upon RS. The technology has the potential to be a mediator of incentives; hence, a better understanding of the interplay of RS development and GPGs can influence decision making, and direct attention and resources to develop or reinforce beneficial RS applications.

It remains an open question whether the potential of RS to intervene in and ease the provision of GPGs can be detected in the very patterns of evolution of the technology. To assess that, we conduct a series of exploratory exercises, using textual information from relevant patent abstracts. We employ structural topic modeling (STM) to draw a granular picture of RS nature and evolution. We identify a series of topics capturing essential features of RS technology, functions, and applications. We then map their evolution to identify structural shifts, and use features of STM to assess the affinity of RS topics to important themes—GPG in the first stance, but also artificial intelligence (AI), the role of public and private actors in RS development, and the international specialization of certain actors (i.e., China) on specific topics.

We find that the direction of inventive activities turns increasingly towards algorithms and the integration of modern methods of data/ image acquisition and analysis, and also that new applications emerge—making the case for looking at RS through the lenses of GPT. Most importantly, our results suggest that RS development features GPG-related elements, which appear in the topic space, even though they are yet peripheral compared to topics mostly including technical terms—an expected result, as patent information has a strong technical focus, rather than an application one. Still, themes related to GPGs play a role in RS technological development. Interestingly, top-ranking topics in what we label the GPG-affinity indicator are, in some cases, overlapping with topics with affinity to AI as well as to public actors, pointing at the fact that a share of technical progress in RS is dedicated to GPG-relevant trajectories. Therefore, we conclude that RS is a technology with general-purpose features and the capability to play a role as a tool in the provision of GPGs.

The paper offers two major contributions. The first is a novel angle of research: to our knowledge, this is the first study that combines a fine-grained analysis of technological evolution with a key theme of political economy, such as GPGs. By connecting these two worlds, we suggest that they can mutually gain: on the one hand, the reach of political economy of GPG can expand beyond the study of incentive structures to delve quantitatively into the role that technology can play to facilitate (or obstacle) the pursuit of global welfare. On the other hand, the economics of technology can begin looking beyond issues of production, adoption, and mere economic impact and explore the quasi-normative implications of the technological evolution on global, humanity-defining dynamics.

The second major contribution is methodological: exploiting features of STM in an innovative way, we generate metadata based on selected terms and use these to build covariates that are specific for the analysis. We label these covariates ‘affinities’ (in our case, to GPG and AI). This is a novel type of indicator, rather flexible and information-rich, that can be reused in further studies.

The paper proceeds as follow: in Section 2, we summarize the theoretical building blocks and the empirical approach we use in the study; namely, we introduce GPT, GPG, and STM. In Section 3, we set the groundwork for our analysis by presenting the dataset, offering a descriptive view on specific relevant terms and topics from our corpus, and setting up the topic modeling exercise. In Section 4, we discuss our findings. Section 5 concludes the paper. We thus contribute to a perspective that increasingly is taken into account in the context of technology analysis.

2. A Framework to Study Remote Sensing

Our goal is to understand the interplay of technology evolution and political economy using the case of RS. In order to conduct our analysis, we outline the theoretical and empirical building blocks we operate with. On the theoretical side, we place RS under the umbrella of the literature studying general purpose technology and global public goods, as both concepts offer interpretative angles to map our phenomenon of interest. On the empirical side, we introduce (structural) topic modeling as a technique to capture the nuances of technological evolution from text data.

2.1. Theoretical Building Blocks

General-purpose technology (GPT). GPTs are well identifiable, usually stand-alone technologies (or clusters of complementary technologies working in close synergy) that are used as an input or tool in a wide range of economic activities. Examples of GPTs are the steam engine, computer platforms, lasers, and especially integrated circuits (Cantner and Vannuccini 2012; Menz and Ott 2011). These technologies are potentially at the core of broader transformations in the whole economic system, and the most radical amongst them set the stage for successive technological eras (Knell and Vannuccini 2012). GPTs are identified through a series of characteristics that make them a peculiar family of breakthrough innovations. The literature discusses several of these—including the absence of technologies that can act as GPT substitutes, or their non-linear impact on productivity (Bekar et al. 2018)—but it tends to converge on three fundamental key features (Bresnahan and Trajtenberg 1995): general applicability (or pervasiveness), technological dynamism, and innovational complementarity (or spawning). General applicability is what allows the use of a technology at scale and across a variety of sectors: a GPT is pervasive because it does "nothing specific" (Simon 1987); in other words, it provides a generic function (i.e., computation, motion and control) to a wealth of user sectors. Technological dynamism refers to the steep learning curve of the technology, as, once realized, the demand for the GPT coming from different sources pushes down its production cost (and pushes up performance) drastically. Finally, innovation spawning captures the enabling capability of GPTs: the use of this technology lowers the barrier (or raises the returns) to conducting innovative activities and, in some cases, opens up new directions and approaches to innovate (i.e., digitization of business models favors firm entry into the app market).

How is the GPT concept relevant to RS? Thoma (2009) discussed the GPT nature of control technologies that enable process automation. In turn, control technologies are enabled by sensors, the same technological component at the core of RS technologies. This suggests that the RS nature might be well approximated by the GPT concept, and its development 'read' through this lenses. We posit that RS technologies have general-purpose features. First, they perform a generic function, that of information acquisition from a distance. Second, this generic function is put at work in a variety of rather heterogeneous application sectors that require measurement and surveying, from meteorology to intelligence and military uses. Third, even though the technology is not new *per se* (for instance, our analysis will cover fifty years of RS patenting), its dynamism increases as a function of the expansion of its uses. Fourth, like many other information-acquisition technologies, RS has the capability to be 'enabling', that is, to induce specific actions (i.e., innovation) by lowering uncertainty or expanding the choice set. The reason for this is that the use of RS produces, at lower costs and/or at a higher quality/coverage, an output (information) that feeds as an input into decision making. This feature of RS can potentially be welfare enhancing; in turn, given the wide reach of the technology, this welfare effect can be *global*, suggesting that next to generality of purpose, RS can play a role in the provision of GPGs.

Global public goods (GPG). GPGs "may correspond to pure or impure public goods that impact much of the world's population." (Buchholz and Sandler 2021, p. 488). They include "identifying virulent pathogens, ameliorating global financial crises, adopting universal regulatory practices, protecting essential ecosystems, allocating geostationary orbits, diverting earthbound planetesimals, preserving cultural heritage, reversing ozone layer depletion, and curbing climate change. These and other GPGs (e.g., eradicating infectious diseases, developing disease treatment regimes, fostering cybersecurity, preserving biodiversity, reducing transnational terrorism, maintaining world peace, discovering scientific breakthroughs, and addressing refugee flows) represent some of the world's most pressing problems" (Buchholz and Sandler 2021, p. 489). When non-excludable but rival, GPGs approximate global commons (i.e., worldwide reservoirs of resources, such as oceans). The well-known sustainable development goals (SDGs) pursued by the United Nations (UN) can be considered a subset of GPGs.

What makes GPGs a distinct family of public goods is their complexity, namely the "multi–actor, multi–sector, multilevel nature of their provision path" (Kaul 2012, p. 736), featuring high transaction costs, high risk of coordination failures, and the need to take into account issues of sovereignty influencing their production and provision. RS can play a supporting role in the provision of GPGs. In fact, Buchholz and Sandler (2021, p. 490) point out that "novel monitoring technologies allow humankind to spot some global public bads (GPBs) and GPGs (e.g., the accumulation of atmospheric greenhouse gases (GHGs), the melting of the planet's icecaps, the health of the world's forests, the state of the stratospheric ozone shield, and the spread of deserts).". This can happen because, as we discuss in the next paragraph, RS provides an input (information) that feeds into decision making, expanding the knowledge set or reducing uncertainty. In other words, RS is a technical tool that can be used to facilitate coordination and that can influence the allocation of resources to the production of GPGs.

Outlook: the economics of RS. In economic terms, the use of RS technology produces an input (information) at lower cost or higher quality (i.e., better scale or resolution). In a growth theory framework, RS adoption can be seen as a production function shifter, that is, a form of capital (or labor, depending on the application) technical change. From this perspective, RS can be instrumental to the provision of GPG—ceteris paribus international cooperation incentives and mechanisms—as it affects the productivity of production factors and, indirectly, the shape of the choice set for decision makers. An alternative way to look at that is to consider RS as a push outwards to the production possibility frontier (PPF) of activities that rely on information acquired from a distance. Forney et al. (2012) illustrate this for the case of groundwater quality surveying using the RS system Landsat.

In sum, RS appears to be a general-purpose, enabling technology, used by both commercial and non-commercial actors, that can produce sizable social returns beyond private returns and shift outwards the possibility frontier of the applications adopting it. This is due to the fact that the information it provides allows for a better use of existing production factors. When used in applications that have global reach, this information represents a form of 'Earth intelligence', which can feed into the production of GPGs. The prominent 'public' role of RS is reflected in how the technology is described by actors pursuing missions with a global 'flavor'. For example, NASA "observes Earth and other planetary bodies via remote sensors on satellites and aircraft that detect and record reflected or emitted energy. Remote sensors, which provide a global perspective and a wealth of data about Earth systems, enable data–informed decision making based on the current and future state of our planet".[2] In the medium to long term, this information will also become important when it comes to proving war events and even war crimes.

2.2. Methodological Approach

A further dimension of our framework to study the nexus between technology and political economy through the case of RS is the methodological one. We trace the presence of GPG-related themes along the technological evolution of RS technology by exploiting information contained in patent documents. Patent data are the natural choice to study the evolution of technology. Despite the never-ending debate about their limitations for economic analysis, patents represent a rich source of data when it comes to unpacking a given technology into its constituent components and techniques. Furthermore, patent data can be exploited to map technology and proximity spaces that capture the interconnections between different 'quantums' of knowledge (Alstott et al. 2016).

Patent data can be used as a source of structured and unstructured information. In our analysis, we focus on the exploitation of the more 'fluid', unstructured information by parsing the text of patents' abstracts using structural topic modeling techniques. This approach allows us to cluster terms retrieved from abstracts into topics, to relate the topic with each others (i.e., using network methods) and to study and track them over time. For example, we can focus on topics (and terms) that are GPG relevant in order to understand to what extent this perspective has permeated RS-related inventions.

The scope of research enabled by the use of text as data cannot be understated. Thanks to advances in machine learning techniques and to digital availability of large corpora of text, textual information is increasingly used to address innovation economic questions. A comprehensive overview on text as data in innovation analyses can be found at Paunov et al. (2018). Gentzkow et al. (2019) provide a recent overview on text as data in economics, while Grimmer and Stewart (2013) address the opportunities and shortcomings of automated text analysis in study political questions. Related, recent overviews are provided by Ranaei et al. (2019) and Van Looy and Magerman (2019), who apply text analysis to study the relationship between science and technology based on papers and patents.

Over the last two decades, probabilistic topic models have become a prominent tool both for processing large amounts of text and for measuring latent variables. The most prominent method is latent Dirichlet allocation (LDA; Blei et al. 2003; Griffith and Steyvers 2004). Instead, in our analysis, we employ structural topic modeling (STM). Unsupervised modeling approaches of text classification imply that there is no need for strong a priori assumptions regarding the outcome. STM represents such an approach, which includes metadata in the classification procedure (compare Roberts et al. 2014, 2016b, 2016a).[3]

STM is a mixed membership model, which implies that the occurrence of topics within documents follows systematic patterns across the whole corpus (Blei and Lafferty 2007; Roberts et al. 2016a). In mixed membership models, documents are not assumed to belong to single topics but to belong simultaneously to several topics, and the topic distributions vary over documents. It also allows to endeavor to seek relationships between different topics across all documents. Generally speaking, STM—like other unsupervised machine learning (ML) algorithms—do not presuppose categories but infer contents from text (see Roberts et al. 2014, who apply STM to open-ended survey questions).

STM applies a so-called bag-of-words approach, i.e., for the analyzed text, the order of words is not considered. Instead, the distribution of words within documents—together with term weights—incorporate essential information on the content of the documents. Topics represent a distribution of words and thus are characterized by the frequent usage of the same vocabulary. The entire corpus can be split in K topics. Another feature of the STM approach is that each document comprises all K topics, though to varying shares.[4] For a given corpus, the distribution of topics, words, and documents can be estimated using Bayesian statistics techniques. Compared to LDA, STM allows for topic distributions to depend upon covariates, which can be selected by the researcher: a feature we will exploit in our analysis.[5]

Aside from covariate information, another key decision to be made refers to the number of topics chosen K, which is not predetermined but must be chosen based on either prior knowledge of the research context or with the help of statistical indicators/diagnostics. In general, high topic numbers increase the validation need while at the same time introducing topics that are too fine and granular to be interpretable in a reasonable manner. Overall, the decision for the topic number faces a trade-off between the topics' separability/exclusivity and their semantic coherence, the latter covering the co-occurrence of words (Mimno et al. 2011). Exclusivity, in contrast, measures how exclusive a term within a topic is compared to other topics (Airoldi and Bischof 2016).

The advantages of automatic content analysis come at the cost that it needs careful validation of the results, a process that cannot be performed automatically. Nelson (2003) argues that automated text analysis is complementary to human knowledge, a statement which is especially true when dealing with unstructured data and latent topics. However, this combination also opens up new research perspectives, such as the proposed link between technology development and GPGs.

3. Empirical Setup

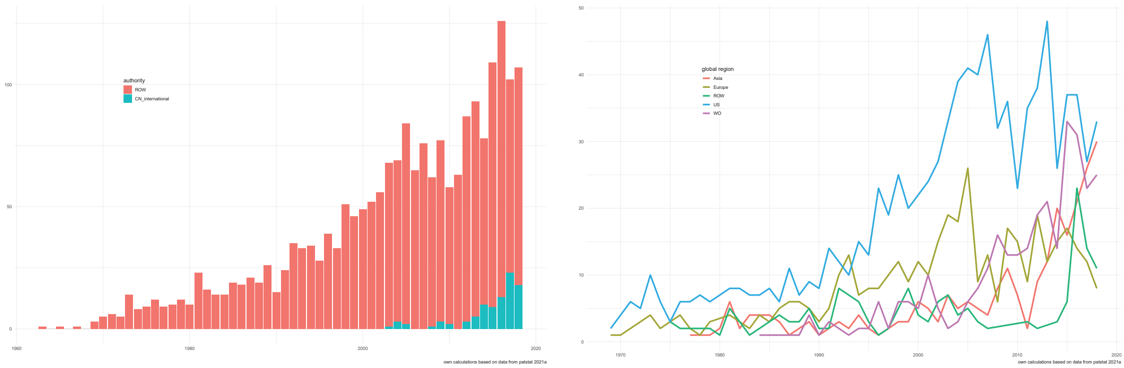
3.1. Overview of the Dataset and RS Technological Profile

Our analysis is based on patent data. Relevant patents are identified by applying a truncated keyword search for the term 'remote sens*' in the PATSTAT 2021a database for the period 1963–2020. Patents are selected if the search term appears in the title OR in the abstract.[6] We only consider patent cooperation treaty (PCT) filings and only the first member of a patent family; moreover, for patents with the first filing at the China Patent Office (SIPO), we restrict our selection only to those patents with a family size of at least 2.[7] Our final sample includes 2.247 unique patent IDs and 2.189 unique abstracts from 24 authorities; we label these 'international patents'. Table 1 summarizes descriptive information of our sample. The column 'all patents' lists all RS PCT patents independent of their family size. It includes 6.618 patents being filed at SIPO only, i.e., with family size 1; the column 'international patents' refers to all filings but only include Chinese patents if their family size exceeds one. For the analysis, we use the unique abstract texts of international patents and restrict the period to 1970–2018. This leaves us with 2.186 patents (i.e., we lose 3 patents due to restricting the period).

Table 1. Sample descriptives of the dataset.

	All Patents	International Patents
unique patent ids	8.865	2.247
unique abstracts	8.807	2.189
unique titles	8.739	2.159
period	1963–2020	1963–2020
authorities	24	24

To ground our analysis, we first explore some properties of the final dataset; in particular, we present filing dynamics and technology classes' coverage. Concerning filing dynamics, Figure 1a shows the evolution of our international patents selection. Patenting in RS increases steadily over time—except for a slump between 2005 and 2010 followed by an even stronger increase—as the technology develops and diffuses. Overall, the US is the main patent authority represented in the sample. However, since 2012, Chinese international filings (labeled as 'CN') have been shaping the worldwide dynamics. This can be see in Figure 1b, which tracks filings from a more continental perspective, distinguishing different 'global regions' and major authorities.[8] Despite filings being dominated by the US, Asia and WO have been catching up, with a boost given by the more recent entry of CN into invention. Europe's dynamics is characterized by steady growth until 2005; after a peak, it experiences a decline.



(**a**) (**b**)

Figure 1. Dynamics of PCT filings world wide and by major global regions and major authorities. CN patents are only included if their family size is at least 2. Compare the appendix for details on the grouping of countries into 'global regions'. (**a**) Evolution of international filings in remote sensing: blue color—CN international filings; red color—all other patents. (**b**) Evolution of PCT filings in remote sensing technologies seen from the perspective of 'global regions' and major authorities: US, Asia (including CN international patents), Europe, WO and ROW.

To capture the technological profile of RS, we can start by exploiting the structured part of patent data, and look at the CPC classes most listed in the patents. These are G06K (graphical data reading), G06T (image data processing or generation), and G01N (investigating or analyzing materials by determining their chemical or physical properties). The classes most cited in RS patents relate to technological components and functions of the technology. This is not surprising, as, to a larger extent, patents are meant to cover information on technical progress in RS. Hence, structured information might overlook applications that have GPG relevance.

Notwithstanding that, some preliminary insights related to our frameworks of analysis can already be drawn. For example, over time, RS-related patents cover an increasing variety of technology classes. This is one of the, admittedly rough, measures characterizing GPTs in the making (Hall and Trajtenberg 2006). Figure 2 depicts the diffusion dynamics of RS-related patents across (top 15 most relevant) CPC classes, making it clear how RS percolates through the technology space over time, gaining purposes and appearing in a wide array of inventions, though to a different extent (captured by the color intensity of the cells).

More important for our purposes is the fact that some of the mentioned classes, even if not dominant in terms of frequency, indicate the *direction* of RS evolution towards certain fields of application. This is the case, for example, of class Y02A (technologies for adaptation to climate change), which is strongly related to GPG themes.

In summary, from an inspection of patents' structured information, we can extract two coarse results: first, RS diffusion across the technology space (approximated by patent classes) shows the general-purpose quality of the technology, rooted in its generic function of information acquisition from a distance. Second, it appears that an intersection of RS and GPG themes exists. While feeble in magnitude, this suggests that some of the uses of the technology have GPG relevance. In order to delve more in depth into this relationship, next, we resort to unstructured data analysis, as it allows for a much more granular assessment of the presence of GPG terms, shaping RS technical developments.

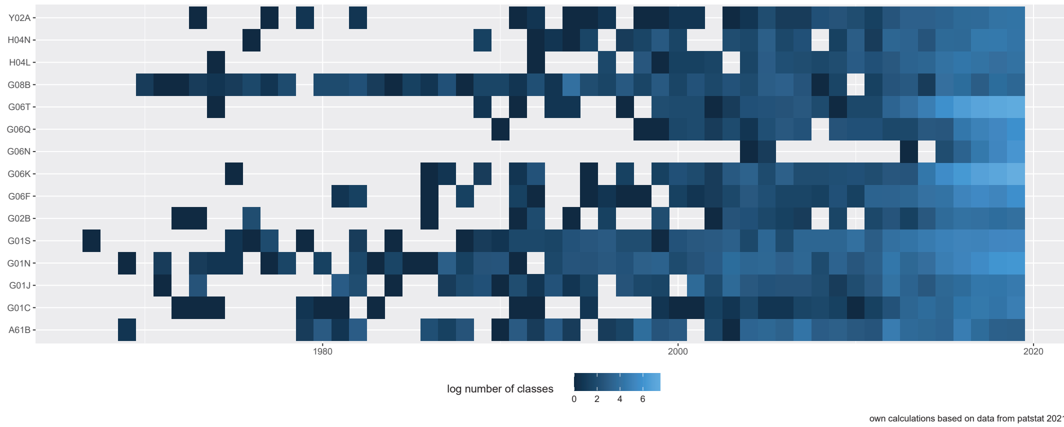


Figure 2. RS-related filing dynamics across the top 15 CPC classes for RS inventions; across time, filings take place in more and more CPC classes, including class Y02A, which is related to climate adaptation.

3.2. Text-Based Analysis: Terms

As a first exercise, we exploit text information by focusing on the dynamics of selected *terms* that we expect carry important signals regarding complementary technologies and domains to RS or fields of application. In Figure 3, we track the frequency of 12 terms over time. The terms refer both to hardware and software complements to RS (i.e., 'drone' and 'neural', respectively) or to specific domains of application of RS (i.e., 'climate' or 'weather') and to specific focus objects of the technology's use (i.e., 'crop' or 'water').[9] We can distinguish between terms that have appeared in the patents' texts for a long time, such as 'data', 'real time', and 'satellite', and those that start being mentioned more recently, for instance 'drone' ('climate') being mentioned in only 7 (10) patents in our dataset. Figure A3 plots the diffusion curves to the topics in which these two terms have the highest impact, and it becomes obvious that both terms are parts in T3.

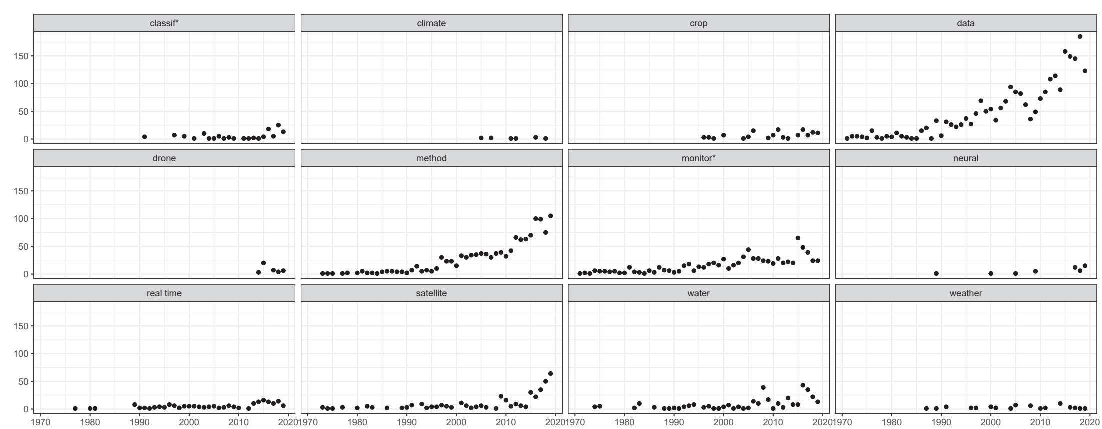


Figure 3. Evolution of selected terms.

Amongst the long-standing terms, we find those capturing the most essential features of the technology. Being a collection of data-acquisition technology, it is not surprising that 'data' appears in this group. What is more interesting is that the same term experiences a continuous increase in frequency, with a relatively recent acceleration. The driver of the dynamics might be related to a novel focus on RS data, now processed through artificial intelligence (AI) algorithms. From this perspective, the appearance of terms such as neural (for neural network) and classif* (including terms such as classifier systems that relate to data-elaboration software), might indicate a growing interdependence between AI and RS technologies, meshing into more complex technology systems offering data collection and elaboration in real time (another term relevant in our sample).

Focusing on the terms that appeared more recently and that do not belong to methods and complementary technologies, our selection includes terms that are fairly relevant both for the diffusion of GPTs and for the provision of GPGs. On the one hand, the recent appearance of a term like drone illustrates the innovational complementarity feature characterizing RS that is embodied by devices (such as drones) that have their own technological trajectory and that can use RS as an 'expansion' of their capabilities. On the other hand, terms such as crop, water, and weather relate to changes in climate or to activities affected by global challenges. The terms water and crop indicate that RS technologies are employed in providing the Earth intelligence we already mentioned, which is instrumental in mapping environmental threats—in turn, a clear global public 'bad'.

3.3. Text-Based Analysis: Structural Topic Modeling

Rationale. We run STM on our corpus. This gives us a granular picture of the technology at the level of words but organized within specific contexts (given by the topics). In other words, with STM, we are able to extract valuable signals from unstructured information. With the topics at hand, we can execute a series of interesting exercises. For example, we can identify shifts within the technology space by plotting topic diffusion curves, which allow to gauge structural shifts within the corpus. Additionally, we can trace the distribution of selected terms across topics—a feature leading back to the GPT issue of pervasiveness. Furthermore, with the use of STM, we can exploit metadata (i.e., covariates obtained from the dataset—a key novelty introduced by this paper—or constructed by the researcher(s)) to impose some structure on the topics and assess whether different issues of interest (i.e., GPG affinity) are relevant or not across the topics. Finally, we can represent information in network form, and apply network metrics to study the topic space. We discuss these exercises in sequence in Section 4.

For the analysis, we restrict our time period to after the year 1970, which reduces our dataset to 2.186 patents with unique abstracts. Concerning model selection, we opt for K (the number of distinct topics the model outputs) $= 42$.[10]

Data preprocessing. We take the texts from the patents' abstracts and apply the following text preprocessing procedure covering these steps: (i) the identification of trigrams and bigrams—only those not including standard stopwords are kept; (ii) the removal of patent-specific stopwords (compare Table A1); and (iii) the running of the STM algorithm, which applies the removal of numbers and punctuation, custom stopwords, and frequent and rare words. The received work with patent data showed that in English texts, ngrams (i.e., conglomerates of n words) often represent technical terms or concepts. At the same time, there is patent-specific 'jargon' in the abstract texts. Since STM is based on text as data, it is crucial to think about how to deal with these specialities. Table A1 in the Appendix A.1 summarizes our selection.

Exploiting information from the covariates. Differently from other text-analysis techniques, such as LDA, STM allows to exploit meta information, which can be created from any variable of the dataset. We use two 'types' of covariates in order to offer a more elaborate analysis of the topics. First, we exploit covariates that are directly linked to variables in the dataset variables. These are as follows:

- Time:[11] This allows us to study the dynamics of the topics and the structural shifts within the corpus. It applies to all 2.186 patents.
- Authority and focus on CN international patents:[12] Patents filed at the Chinese patent authority (SIPO) and with a family size of 2 or more as discussed in Section 3.1. This allows to control for the recent filing boom in RS, and to assess whether there is a (macro)

geographical specialization in certain topics. The split of the 2.186 patents through this covariate shows that in our dataset, 113 patents (5.2%) are CN international patents.

- Sector assignment—private sector filings vs. non-private sector filings:[13] The split of the 2.186 patents through this covariate shows that in our dataset, 1.561 patents (71.4%) may be assigned to the private sector (covering companies and individuals); 302 patents (13.8%) may be assigned to the non-private sector (covering non-profit and university), and for 323 patents (14.8%), no sector information is available. In the analysis, the latter are dropped.

Second, we use term-based covariates. These represent the key novelty of our analysis. In fact, through term-based covariates, we create meta information based on criteria that are relevant to our research question and that we define normatively. In particular, we build two families of covariates, one capturing the affinity of the reach topic to GPG, and the other to AI. Affinity is based on the inclusion in a patent abstract of at least one of the terms in Table 2. Our sample is split as follows along the covariates:

- GPG affinity 521 patents with GPG affinity (23.8%); 1.665 (76.2%) without GPG affinity.
- AI affinity given in 72 patents (3.3%); 2.114 patents (96.7%) without AI affinity.

Note that we can exploit this meta information even for rather small sub-samples of patents, e.g., compare the little number of 72 patents in the case of AI affinity.

Table 2. Term-based covariate creation for GPG affinity and AI affinity.

Covariate	Terms
GPG affinity	'agriculture', 'air', 'clean', 'climate', 'CO_2', 'crop', 'crops', 'dioxide', 'ecological', 'ecology', 'fire', 'fires', 'flood', 'food', 'heat', 'nitrogen', 'sulfur', 'water', 'wildfire', 'wildfires'
AI affinity	'classified', 'classifier', 'classification', 'classify', 'classifying', 'misclassification', 'neural', 'preclassified', 'reclassification', 'supervised', 'unsupervised'

GPG affinity is the key dimension of interest for this paper. Introducing the covariate, we can estimate the closeness of each of the 42 topics to GPG-related terms to assess, for instance, how 'central' GPG-relevant topics are within the whole corpus. We decide to introduce further term-based covariates capturing AI to measure another characteristic of RS evolution: as discussed in Section 3, RS evolves as a technology system, in synergy with complementary technologies. AI is, among other things, a collection of software technologies for data processing (Vannuccini and Prytkova 2021), and data processing is the natural complement to the data acquisition function performed by RS. In fact, structural shifts in terms and topics relevance in RS can be driven by the increasing transition towards AI techniques used to manipulate remote-sensing-acquired data.

Outcomes of the K42 model. Figure 4 lists for the full period of analysis the topics extracted from our sample, ranked by expected topic proportions, and includes the 15 most important terms per topic. The top ranking topics are T22, T20, T28, T15, T33. As it could be expected, these relate to technical features of RS technologies, and represent the core of the invention direction in RS. Terms related to RS functions—in particular, data acquisition—also rank high, with T28 included in the top 3. However, when looking at the their dynamics, we see an increase in T28 (most important term: data) and a T15 (most important term: light), whereas the other big topics see a sharp decline. Table A2 in the Appendix A.2 presents the same information, ordered by topic number and for 17 terms.

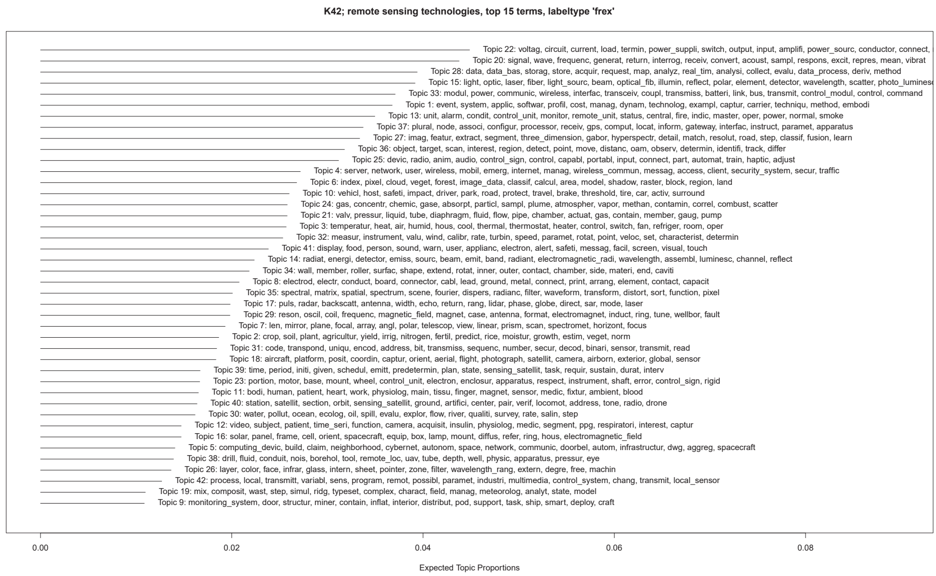
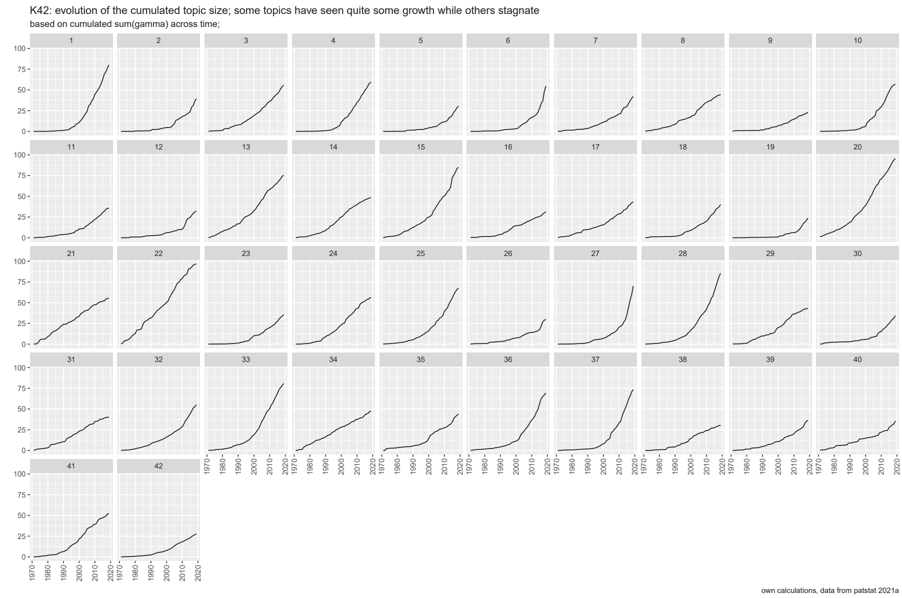


Figure 4. Expected topic proportion and the top 15 terms per topic for the K42 model; the expected topic proportion represents the importance of the topic in the corpus for the full period of analysis (it results from the γ matrix (per-document-per-topic) and is the sum of the γ values per topic divided by the sum of all γ values).

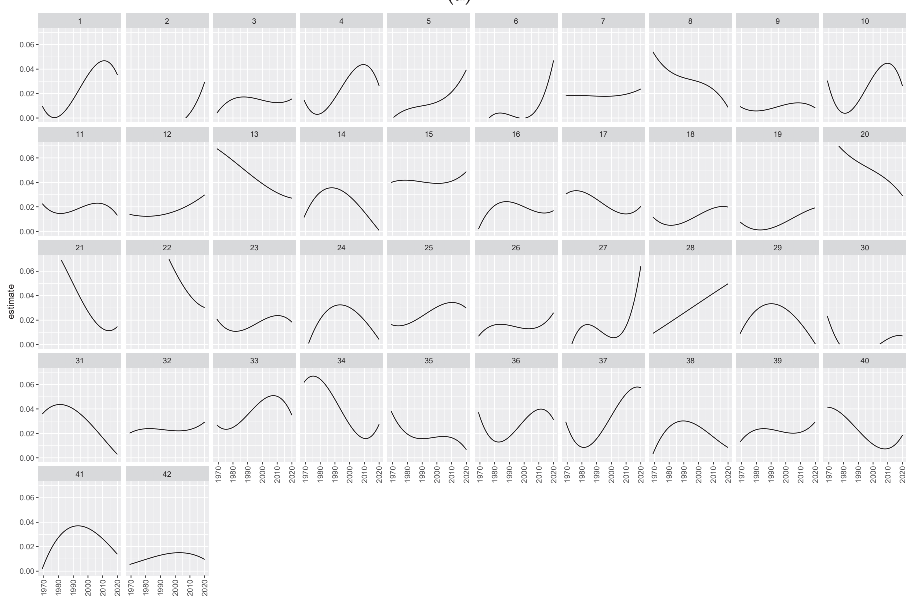
4. Results and Discussion

With some early insights on terms dynamics and the K42 model outcome at hand, we can now engage in a series of exercises to form a better picture of the RS nature, evolution, and propensity to be a medium for GPGs, amongst other things. First, we focus on the topic dynamics. Second, we look at the distribution of selected terms across topics. Third, we exploit our meta-information on covariates to study the affinities of specific themes to RS, including GPG and AI. Finally, we present the topic space as a network and compare different network metrics to identify, for instance, central and peripheral nodes.

Dynamics. In Figure 4, we can see the relative importance of the 42 topics (as represented by the topic proportion) as well as the most important terms per topic over the whole period. We now focus on their evolution. Figure 5 presents the trends of (cumulated) topic size in the top panel (Figure 5a), and topic dynamics in the bottom panel (Figure 5b). Concerning size, all topics display an increase that trails the very increase in the patent corpus. However, some topics' size growth tends to stagnate or to show an inflection point; this is the case, for instance, of T29 and T38. Both contain technical elements that might have already achieved a standardized configuration, and thus feature a slowdown in innovation. Alternatively, these topics could capture 'reverse salients' for the overall technology development. The structural shifts of topics over time become evident when inspecting the dynamics in Figure 5b, with certain topics relatively losing relevance and others gaining a more prominent role. This is the case for topics such as T6, T27, or T28 that cover issues related to image processing and data and have, thus, a more software-related nature. Their positive gradient already suggests that along the evolution of RS technology, the relative weight of physical vs. intangible components is shifted in favor of the latter, as the increasing diffusion of RS across different domains is grounded on the possibility to elaborate the data acquired by RS hardware. The relevance of the different topics is heterogeneous across global regions and major authorities. Figure 6 plots the spatial distribution of the topics evolution. Asia drives the dynamics in topics such as T6 and T27 that, as we will see, are related to advances in image recognition (in turn, a key application field for AI systems).



(**a**)



(**b**)

Figure 5. Evolution of topics for the K42 model and the full period: cumulated size (corpus growth) and dynamics (corpus structure). (**a**) Cumulated topic size across time (the sum of γ-values per topic cumulated over time); (**b**) topic dynamics across time. For each year the expected topic proportions sum up to 1. These dynamics have to be interpreted in light of the steadily increasing number of patents.

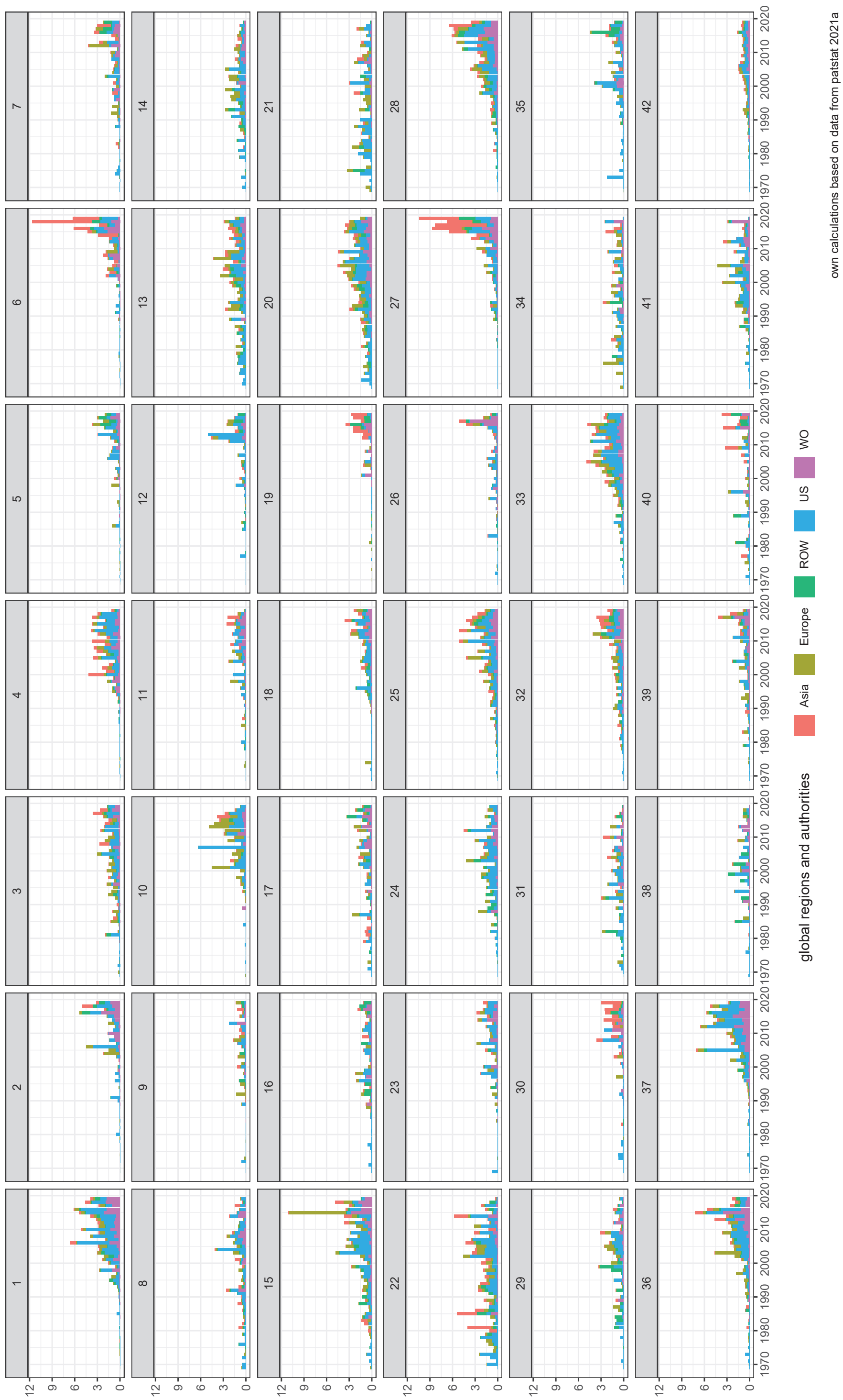


Figure 6. Spatial distribution related to the topic evolution, K42 model; for each topic, the up to three global regions or authorities which display the highest sum of γ-values are reported. Compare also the discussion related to CN affinity, e.g., in Figure 9.

Terms distribution across topics. In Figure 7, we plot the distribution of the terms' appearance across the topics for the full period. We focus on three selected terms, 'drone', 'real-time', and 'satellite'. The support of the figure is the 42 topics (for each term). This gives us some insight regarding the pervasiveness of some themes related to RS development. For example, the term drone is very 'localized' in a handful of topics. This might be related to the specific hardware-related synergies it develops with RS technology but also to the fact that it is a relatively novel feature in RS patents' texts as shown in Figure 3. We also see a strong embeddedness in T40—which thus bridges the terms 'drone' and 'satellite'. In contrast, real-time and satellite have a long-standing presence in the sample; however, they differ in spread across the topics. Real time is a pervasive term that appears in patents featuring diverse topics; this is certainly due to the fact that the speed of data acquisition has been and continues to be a key characteristic of RS, especially when considering intelligence and military uses, but also GPG-related uses, such as the monitoring of severe weather events, refugees flow, or cybersecurity threats. In contrast, satellite is a not as widely spread across topics—possibly because of its specific technological trajectory—but has experienced a sudden acceleration in frequency in recent periods (compare again Figure 3). This could be related to an increasing global focus of RS inventions, as well as to related trends in the private commercialization of Low-Earth-Orbit activities. In summary, through this exercise, we can obtain granular insights on the technological nature of RS—for example, emerging inventions driven by 'hardware' complementarities (drones), persistent and pervasive inventive activity based on the 'service' that RS technology delivers (real time), and growing inventions related to terms directly linked to the provision of Earth intelligence, monitoring and related services, and, thus, also to GPGs (satellite).

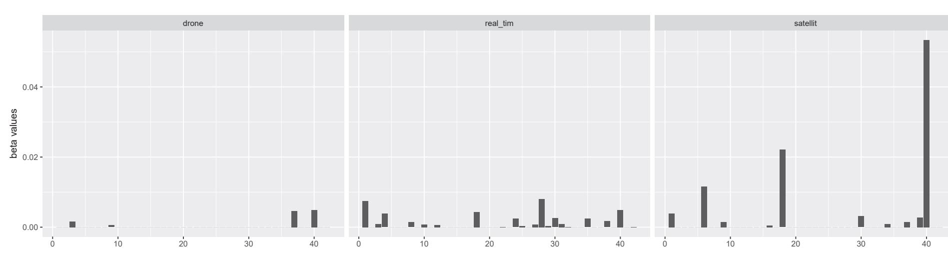
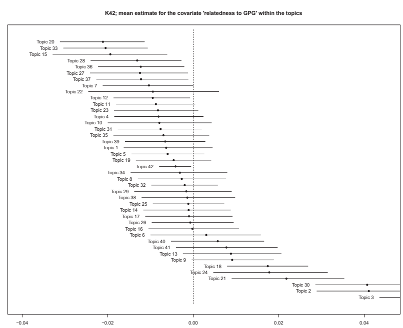
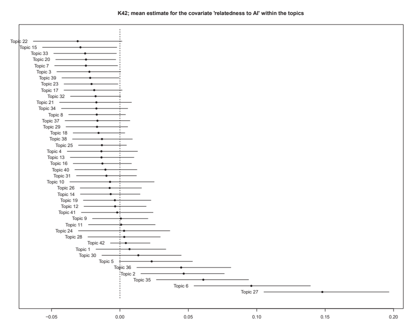


Figure 7. Term distribution across topics based on β-values; full period. Recall: The term 'drone' is recent and rare; 'satellite' is established and has seen quite some dynamics; 'real-time' is established and did not experience dynamics (compare also Figure 3).

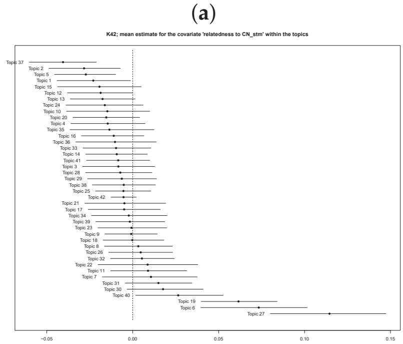
Affinities. In Figure 8, we present the mean estimates of affinities for all topics and all four types of covariates: GPG (panel (a)), AI (panel (b)), public/private sector (panel (c)), and China origin (panel (d)). This allows us to compare topics relevant for each covariate type and to explore co-occurrencies. We start with GPG covariates. The topics with the highest estimated mean affinitites are T3, T2, T30, and T21. T2 and T30 are particularly relevant, as they include among their top terms several that are clearly related to global challenges, such as crops, soil, and agricultural activities (T2), or water, oil and ocean (T30). A visual depiction of the key terms for the structural shifts of the top four topics by GPG affinity is offered by the word clouds in Figure A1 and the diffusion curves in Figure A2, both in the Appendix A.3. Looking at the top topics in terms of AI affinity, we find T27, T6, T35, and T2. Here, key topics from a pure AI standpoint are T27 and T6, which include terms related to image processing (i.e., feature extraction)—the main AI capability used in RS. However, T6 also includes terms that have to do with specific uses of RS in the environmental domain and that can have potential global reach, such as forest and veget*.[14] Importantly, T2 co-occurs also as a top GPG-relevant topic. This illustrates an important overlap: some inventions in RS that involve AI have GPG-related application, showing technological synergies at work for global uses. When focusing on affinity to public actors (the left side of the support of panel (c); the right side captures affinity to private actors), the top topics are T2, T35, T27, and T6. These perfectly match the top topics for AI affinity, suggesting that—at least in the field of RS inventive activities—patents involving AI are also more related to public actors. This is a further piece of evidence to understand the RS-GPG nexus: public actors are often (even if not exclusively) the key actors involved in the production and provision of (global) public goods. In contrast, private actors' affinity is higher on topics such as T22, T13, T10, and T4, which mostly refer to the specific hardware components of RS technology, and thus likely capture invention along the supplier chain of RS. Finally, we can offer some preliminary insight on whether there are signs of international specialization in RS invention by inspecting the mean estimates on China affinity. In this case, the top four topics are T27, T6, T19, and T40. We see that T27 and T6 are ranked top in affinity with AI covariates and non-private actors' covariates. From a political economy perspective, China develops RS technology through the initiative of public actors, in directions strongly related to AI. RS appears again as a globally relevant technology, whose progresses are possibly pushed by a key emerging geopolitical actor. An additional support to this idea comes from another topic ranking high in China-affinity estimates, T40, which covers satellite technology—needless to say, a strategic and global one.



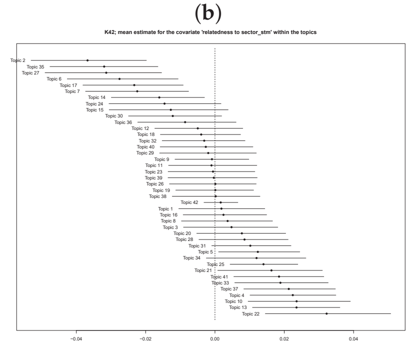
(**a**)



(**b**)



(**c**)



(**d**)

Figure 8. Identification of affinities. The mean estimate split allows to assign topics to selected affinities (vertical line depicted at the level 0). The dot represents the mean estimate value, and the horizontal line reflects the 95% confidence interval. The topic numbers mentioned in the subpanels are those showing a clear affinity to either perspective. They are used for the color-coded network in Figure 9. Related to sector affinity, the color code involves both perspectives, namely private sector affinity and non-private sector affinity. For the affinities in panels (**a**–**c**) only those with clear positive values are taken into account in the network. (**a**) GPG affinity: topics 3, 2, 30, 21, 24, 18, 9; (**b**) AI affinity: topics 27, 6, 35, 2, 36, 5; (**c**) CN affinity: topics 27, 6, 19, 40; (**d**) private sector affinity: private sector topics 22, 13, 10, 4, 37, 33, 41, 21, 25; non-private sector topics 2, 35, 27, 7, 17, 14.

Merging all perspectives. The insights we derived from the discussion of the affinity measures become more evident when topics are presented in network form. In Figure 9, we present the RS topic network, created by linking topic-sharing terms.[15] We color code the network to highlight top ranking topics in terms of affinity indicators, as introduced in the previous paragraph. From visual inspection, we can confirm some overlap between topics showing high GPG, AI, public actors, and China affinity. As discussed, private actors seem to conduct inventive activities more focused on RS component technologies, while non-private inventors have high affinity with some topics that are also GPG and AI related, suggesting that RS can be instrumental to GPGs when invention is initiated by the classic providers of public goods. Furthermore, we could speculate that GPG-relevant invention trajectories might give rise to private coordination failures, and thus require initial public support; this argument goes in line with the failures characterizing the kick-off phase of GPT diffusion (Bresnahan and Trajtenberg 1995). Such a perspective can be supported by noting that GPG-related topics are yet rather peripheral in the topic network.

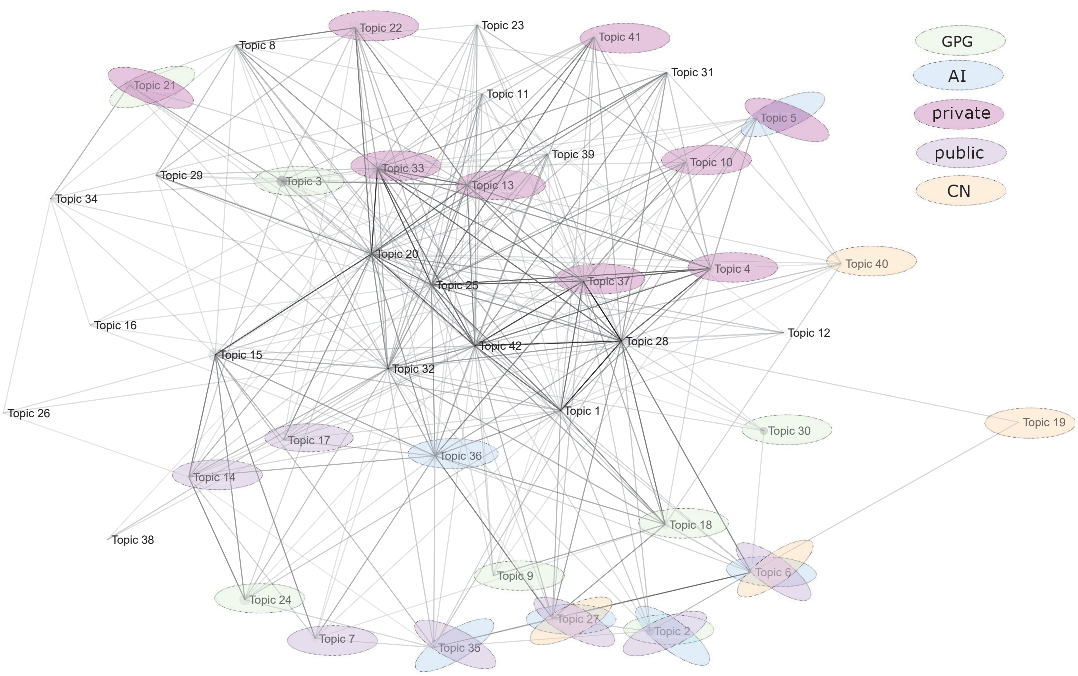


Figure 9. Topic network of the K42 model including all the dimensions of our analysis (the covariates), depicting (when present) the overlap of some topics across different perspectives; the color code is based on the mean estimates derived in Figure 8.

To provide more quantitative support to our claims, we can exploit network analysis and compute metrics on our topic space. Figure 10 presents a correlation plot of different network metrics (size, degree centrality), our affinity indexes, and topic dynamics. We confirm that the private sector inventors are negatively correlated with AI, which instead correlates positively with China patenting, making the case for some specialization in inventive activities taking shape internationally. GPG affinity is negatively correlated with degree, thus supporting the idea that GPG-related technological advances as captured by topics are yet a peripheral development. This is to be expected to a certain extent: in fact, GPG terms will relate with high likelihood to uses of RS, which are less frequently mentioned in patents' abstracts compared to the technological core of the patented inventions.

However, we stress that for a topic being peripheral in the topic space does not mean being irrelevant; on the contrary, our methodology allows to pick up emerging trends, with RS uses (including those that have GPG valence) increasingly appearing in the documents.

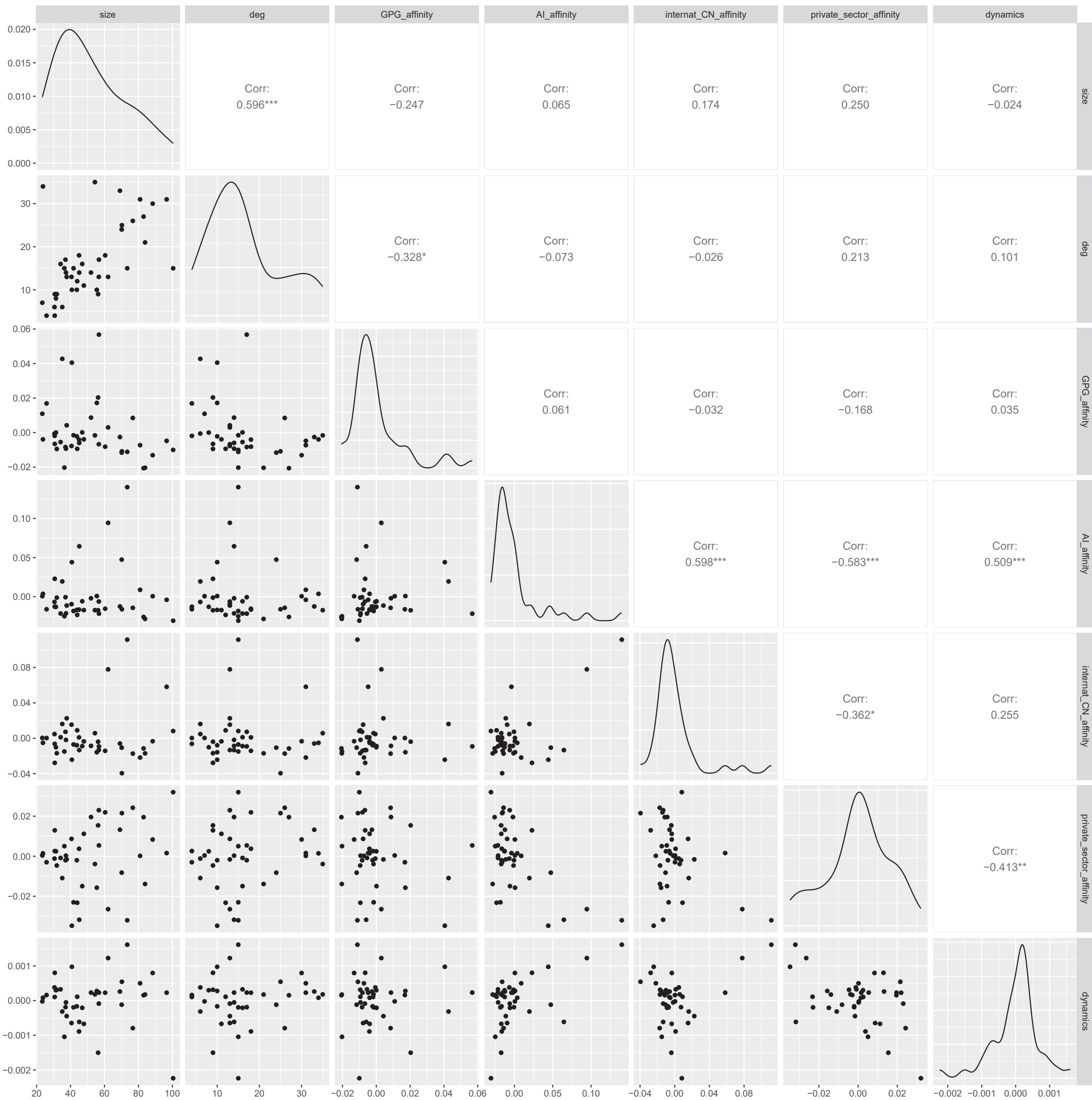


Figure 10. Correlation plot of topic network metrics: size, degree, GPG affinity, AI affinity, CN affinity, private sector affinity, and dynamics. *, **, *** indicate statistical significance levels at respectively 10%, 5% and 1%.

5. Conclusions and Outlook

In this paper, we studied the relationship between technological change and political economy issues using the case of remote sensing technology and the theme of global public goods. RS is a collection of information acquisition technologies, whose generic function can be applied to several goals, including some that have a global reach or impact. An example is the monitoring of climate and environmental changes. RS is an important technology, as it displays the properties of a GPT—a type of innovation with transformative impact.

Our motivation for the study was to assess whether the fact that RS technology can influence the provision of GPG could already be detected from the direction of invention in RS, proxied by patenting. We employed structural topic modeling (STM) to exploit information from unstructured data (abstracts' text corpus) over an extensive time period. Our methodology has two main advantages: first, it provides us with granular information to explore the nexus between RS and GPG. Second, we could use metadata to build covariates that allow exploring specific aspects of RS invention dynamics: in particular, we estimated an indicator of topics' affinity with GPG and studied its relationship with other topics' features, such as affinity to AI technologies, public inventors, or inventive activities in a growing dynamic economy like China. We found that GPG-related topics are peripheral in the RS patents topic space, and yet they are emerging, suggesting that RS does play a role in how global public provision is deployed. It goes without saying that our approach has shortcomings too: for example, and despite our robustness checks, the choice of the topic number parameter has a degree of arbitrariness. In general, we are able to draw inference from a snapshot of terms distribution across topics, but we cannot identify specific mechanisms shaping the RS-GPG relationship.

We focused on tracing a theme of political economy into technical documents; hence, it is not our goal to address 'classic' issues related to public goods provision, such as the solution of coordination failure and the design of incentives. However, with our results, we shed light on the fact that a given technology can be instrumental in the pursuit of global goals. As societal challenges become increasingly pressing, this will provide fertile ground for continued growth in RS patent-filing activities, shaping its direction of invention.

The analysis we conducted is a first step to single out whether and how a given technology crosses aspects that are GPG relevant during its evolution. In this sense, this paper is a novel but also exploratory contribution. We hope to direct research and policy attention towards the fact that under the bridge that connects technology and GPGs, there are interesting issues worth further investigation.

As we focus on technical information and on the presence of GPG terms in it, we are not able to delve into the ethical and legal aspects of RS uses. However, an important aspect not to leave aside is if RS could be considered a dual-use technology (Forge 2010): in fact, the generic function of information acquisition from a distance can feed both positive and harmful uses. It goes without saying that the many purposes of RS range from humanitarian to military and intelligence ones. RS has the potential to contribute positively to the production of GPGs; however, scenarios in which its use entails (global) welfare reduction can also be imagined, from surveillance to espionage, terrorism and corporate data capture. While it is problematic to infer the desired uses of technology from patent documents, even at a granular level of analysis, this possibility makes even clearer the relevance of combining the technological and the political economy perspective in innovation research, and should inspire further studies along this trajectory.

Author Contributions: I.O.: conceptualisation; analysis and results interpretation; writing. S.V.: conceptualisation; analysis and results interpretation; writing. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The patent data has been taken from the patstat database 2021, spring version. The list of the patent IDs utilized for analysis can be provided upon request.

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

Appendix A

Appendix A.1. Data Preprocessing

Table A1 collects all ngrams and specific stopwords used to preprocess our text corpus.

Table A1. K42 data preprocessing: ngrams, patent-specific and technology-specific stopwords.

Context	Terms
trigrams	'convolutional neural network', 'light emitting diode' 'local sensor data' 'synthetic aperture radar', 'unmanned aerial vehicle'
bigrams	'base station', 'central control', 'computing device', 'control circuit', 'control device', 'control module', 'control signal', 'control system', 'control unit', 'data base', 'data collection', 'data processing', 'database' 'earth's surface', 'electric power', 'electromagnetic radiation', 'electronic device', 'high resolution', 'image data', 'land use', 'light beam', 'light emitting', 'light source', 'local sensor', 'magnetic field', 'management system', 'measurement data', 'monitoring system', 'multi scale', 'multi-spectral', 'neural network', 'optical fiber', 'optical remote', 'output signal', 'output voltage', 'power source', 'power supply', 'processing system', 'processing unit', 'radio frequency', 'real time', 'remote location', 'remote unit', 'satellite data', 'security system', 'sensing apparatus', 'sensing satellite', 'signal processing', 'wavelength range', 'wireless communication'
custom stopwords	'along', 'also', 'and/or', 'art', 'can', 'claim', 'claiming', 'claims', 'comprise', 'comprised', 'comprises', 'comprising', 'contain', 'contained', 'containing', 'contains', 'correspond', 'corresponding', 'corresponds', 'describe', 'described', 'describes', 'describing', 'directed', 'disclose', 'disclosed', 'discloses', 'disclosing', 'first herein', 'include', 'included', 'includes', 'including', 'invention', 'least', 'like', 'may', 'obtain', 'obtained', 'obtaining', 'obtains', 'one', 'permit', 'permits', 'present', 'presented', 'presenting', 'presents', 'prior', 'provide', 'provided', 'provides', 'providing', 'relate', 'related', 'relates', 'relating', 'said', 'second', 'see', 'shown', 'thereof', 'two', 'wherein', 'within'
technology specific stopwords	'remote', 'sensing', 'sensor'

Appendix A.2. Topics, Terms and Prevalence Ordered by Topic Number

Table A2 lists the 42 topics by number, the topic prevalence and the top 17 terms for each topic.

Table A2. Topics, terms and prevalence, ordered by topic number (K42 model).

Topic	Topic Proportion	Terms
Topic 1	0.0368	system, method, use, detect, embodi, applic, base, util, event, exampl, perform, monitor, determin, manag, improv, particular, implement
Topic 2	0.0186	crop, field, use, plant, agricultur, yield, soil, irrig, predict, determin, estim, base, area, nitrogen, veget, applic, fertil
Topic 3	0.0257	air, hous, control, use, cool, fan, sensor, switch, instal, batteri, enclosur, mount, inlet, valu, assembl, respons, cooler
Topic 4	0.0272	network, wireless, server, user, sensor, receiv, transmit, local, monitor, transceiv, inform, devic, communic, mobil, internet, via, central
Topic 5	0.0141	system, communic, devic, build, computing_devic, network, claim, user, function, cybernet, applic, embodi, oper, level, report, util, adapt
Topic 6	0.0268	imag, area, method, pixel, model, base, cloud, surfac, index, veget, satellit, region, calcul, forest, classif, image_data, differ
Topic 7	0.0193	mirror, len, imag, plane, array, angl, platform, focal, surfac, element, optic, infrar, field, light, camera, secondari, spectromet
Topic 8	0.0208	electr, electrod, ground, element, connect, conduct, plural, print, form, thermal, circuit, common, arrang, compon, lead, singl, head
Topic 9	0.0109	structur, monitoring_system, support, door, mount, use, system, deploy, inflat, task, interior, distribut, adapt, damag, attach, pod, caus
Topic 10	0.0260	vehicl, detect, determin, devic, impact, signal, driver, system, road, activ, inform, park, arrang, brake, respons, track, emiss
Topic 11	0.0165	bodi, sensor, patient, detect, use, analyt, posit, human, medic, blood, inform, magnet, physiolog, heart, user, fixtur, devic
Topic 12	0.0147	video, subject, use, method, determin, function, field, region, interest, loss, camera, reconstruct, time_seri, patient, electr, estim, acquisit
Topic 13	0.0350	unit, alarm, monitor, power, control_unit, oper, electr, control, central, sensor, condit, remote_unit, transmit, system, connect, suppli, master
Topic 14	0.0224	detector, radiat, energi, sourc, assembl, illumin, emit, reflect, detect, locat, beam, configur, region, mirror, infrar, filter, remot
Topic 15	0.0392	optic, light, element, fiber, optical_fib, receiv, reflect, light_sourc, polar, beam, environ, arrang, monitor, coupl, output, end, system

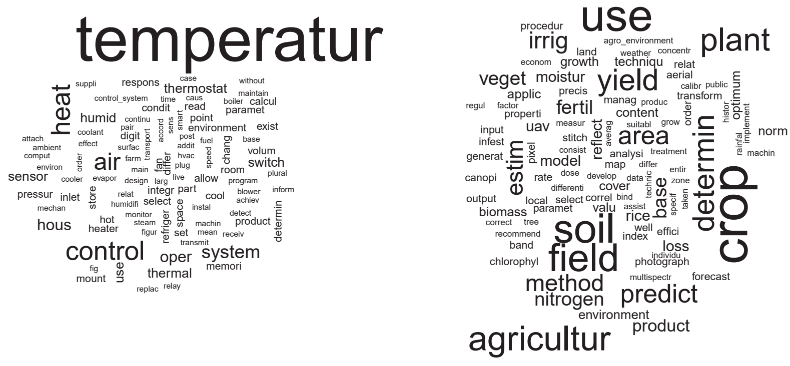
Table A2. *Cont.*

Topic	Topic Proportion	Terms
Topic 16	0.0147	solar, frame, panel, orient, cell, posit, sourc, refer, generat, element, bodi, use, compon, plural, electromagnetic_field, diffus, magnetic_field
Topic 17	0.0198	puls, radar, time, rang, receiv, transmiss, devic, lidar, return, transmit, mode, backscatt, echo, interv, direct, method, oper
Topic 18	0.0184	posit, aircraft, platform, sensor, distribut, inform, aerial, satellit, orient, comput, exterior, configur, airborn, area, ground, camera, process
Topic 19	0.0110	step, index, method, mix, use, composit, wast, differ, color, calcul, accord, typeset, manag, field, medic, waveguid, photo
Topic 20	0.0438	signal, frequenc, return, beam, generat, compon, sampl, vibrat, detect, excit, phase, system, receiv, nois, interrog, repres, probe
Topic 21	0.0258	pressur, valv, control, tube, gas, flow, connect, fluid, chamber, actuat, suppli, liquid, posit, end, pump, locat, pipe
Topic 22	0.0449	voltag, circuit, current, output, connect, load, sens, termin, power_suppli, input, control, power, amplifi, switch, detect, suppli, appli
Topic 23	0.0167	base, portion, control_unit, electron, receiv, determin, vehicl, control, respect, adjust, indic, mount, use, configur, system, instrument, generat
Topic 24	0.0258	gas, detect, use, concentr, filter, atmospher, absorpt, plume, correl, gase, particl, vapor, chemic, combust, path, contamin, method
Topic 25	0.0312	devic, radio, antenna, receiv, sound, signal, connect, input, wave, transmit, direct, transmiss, frequenc, consist, use, dwg, control
Topic 26	0.0137	layer, filter, zone, intern, face, infrar, devic, sheet, mode, extern, wavelength_rang, glass, conduct, motor, select, input, assembl
Topic 27	0.0334	imag, featur, method, extract, inform, result, segment, accord, process, step, road, use, resolut, high, characterist, perform, target
Topic 28	0.0394	data, store, receiv, generat, method, collect, process, storag, data_bas, time, acquir, sensor, transmit, analyz, locat, processor, analysi
Topic 29	0.0198	reson, frequenc, magnet, coil, format, case, magnetic_field, materi, antenna, characterist, condit, method, array, form, wellbor, electromagnet, element
Topic 30	0.0162	water, method, use, bodi, oil, flow, ocean, apparatus, step, surfac, spill, mount, equip, qualiti, determin, rate, explor
Topic 31	0.0184	code, sensor, transpond, transmit, transmiss, differ, encod, uniqu, valu, time, use, bit, secur, signal, respons, period, control_circuit
Topic 32	0.0253	measur, valu, instrument, calibr, paramet, set, rate, determin, point, rotat, devic, connect, mechan, axi, drive, use, character
Topic 33	0.0371	modul, communic, configur, devic, power, interfac, control, receiv, transmit, mode, coupl, bus, oper, batteri, command, condit, environment
Topic 34	0.0218	surfac, end, member, posit, materi, shape, shaft, extend, rotat, mechan, side, contact, wall, oper, portion, machin, locat
Topic 35	0.0201	spectral, imag, spatial, use, matrix, filter, process, function, pixel, band, vector, soil, scene, reflect, spectrum, method, refer
Topic 36	0.0318	object, target, detect, scan, point, determin, reflect, field, region, method, use, interest, distanc, wave, area, direct, rang
Topic 37	0.0337	plural, associ, node, receiv, comput, locat, apparatus, activ, gps, paramet, respect, devic, sensor, interfac, determin, processor, inform
Topic 38	0.0139	drill, apparatus, use, method, fluid, underground, orient, surfac, detect, equip, nois, physic, sensor, well, posit, depth, pressur
Topic 39	0.0167	time, laser, schedul, output, emitt, task, devic, plan, detector, given, sensing_satellit, method, materi, coil, nois, requir, use
Topic 40	0.0164	station, inform, control, section, transmit, communic, ground, satellit, receiv, center, central, monitor, relay, address, sensing_satellit, condit, level
Topic 41	0.0238	display, emerg, user, electron, monitor, level, locat, use, area, screen, messag, result, presenc, liquid, hand, audio, inform
Topic 42	0.0127	process, fluid, function, oper, communic, devic, pressur, end, transmitt, conduit, path, program, control_system, cloud_bas, movement, fill, base

Appendix A.3. Breakdown of Global Regions

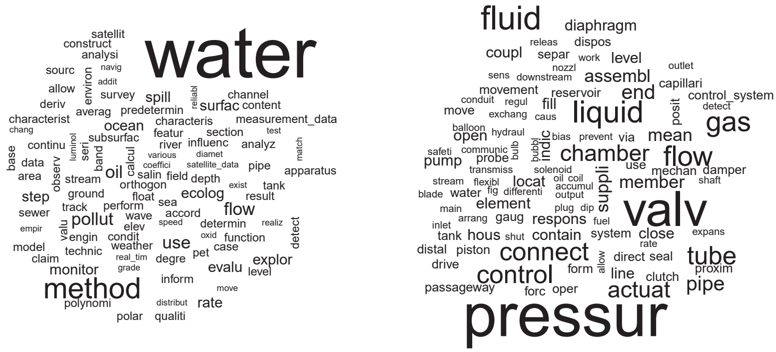
The pooling of the 24 patent authorities into 'global regions' as reported in Figures 1b and 6 is as follows (the United States and WO are not composite lists but represent authorities):

- 'Asia' includes the authorities of Japan, Korea, China, and Taiwan;
- 'Europe' covers the European Patent Office (EPO) and the authorities of Austria, Belgium, Bulgaria, France, Germany, Greece, Ireland, the Netherlands, the United Kingdom, Romania, Spain, and Switzerland;
- 'ROW' (Rest of World) includes the authorities of Australia, Asia/Pacific, Eurasia, Canada, New Zealand, and Russia.



(**a**) (**b**)

Figure A1. *Cont.*



(**c**) (**d**)

Figure A1. Word clouds related to topics with GPG affinity; the size of the term represents its relative importance within the topic. We see some application fields but also that the technical perspective plays a role. (**a**) Topic 3; (**b**) topic 2; (**c**) topic 30; and (**d**) topic 21.

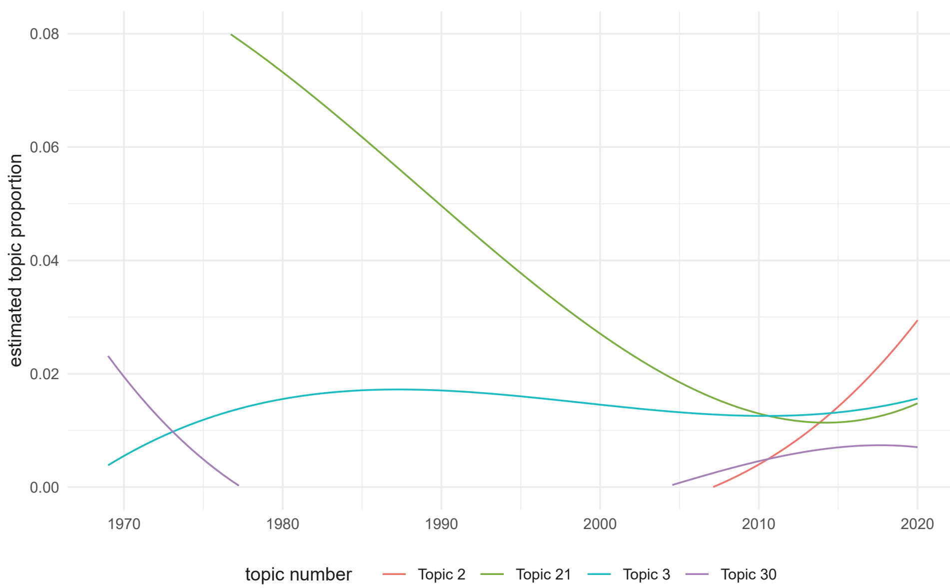
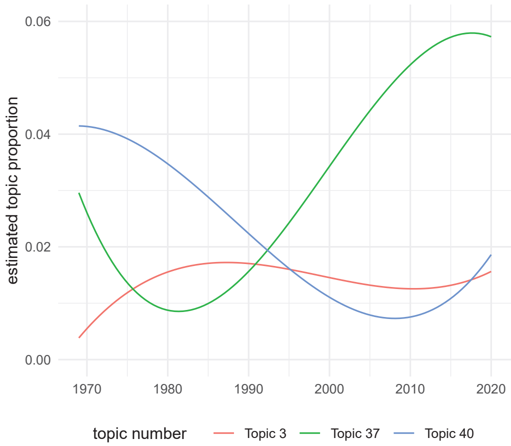
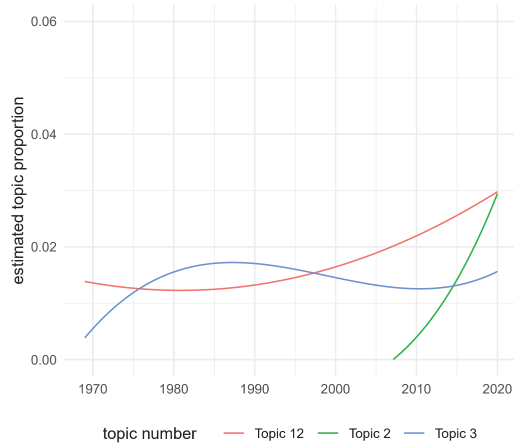


Figure A2. Structural shifts of topics with GPG affinity; compare also word clouds in Figure A1.



(**a**)



(**b**)

Figure A3. Diffusion curves of the topics which have the highest β values for the selected terms (note that the diffusion curve of T3 is colored in red in panel (**a**) and colored in blue in panel (**b**)). (**a**) 'drone': topics 40, 37, 3; (**b**) 'climate': topics 2, 12, 3.

Notes

1 https://en.wikipedia.org/wiki/Remote_sensing, Wikipedia, accessed 13 March 2023.

2 https://www.earthdata.nasa.gov/learn/backgrounders/remote-sensing, accessed on 13 March 2023.

3 Roberts et al. (2013) develop the STM which exploits document-level covariates affecting topical prevalence and/or topical content. The authors especially provide an R package (stm), which allows users to incorporate the specific structure of their corpus and thus to directly estimate the quantities of interest in applied problems. The approach to including the corpus structure intends to make inference about observed covariates rather than predicting covariate values in unseen text.

4 The generative process of each document can be understood as a procedure that (i) draws a document length, then (ii) word by word, draws a topic from the distribution of K topics, (iii) draws a word from the associated distribution, and (iv) proceeds with the following word. For a given set of documents, the underlying distributions can be estimated using Bayesian statistics techniques. Details on the generative process can be found in Blei et al. (2003).

5 The basic assumption is that the mean prevalence of a topic, i.e., its share in all documents at a given point of time, can be expressed by splines. A spline is a function defined piecewise by polynomials. In the STM package in R, the default is set to $d = 3$, i.e., piecewise third-degree polynomials allow for non-linear changes over time. This allows to avoid erratic behavior at the domain bounds.

6 While designing the concept of our technology breakdown, we also carried out cooperative patent classification (CPC) class search at ESPACENET based on the term 'remote sensing'. However, that did not provide additional information or insights. Compare EPO et al. (2022) for a CPC class-based technology breakdown to capture the technology field of space-borne sensing.

7 Overall, the term search resulted in 8.807 unique patents. We detect an exorbitant increase in filings after 2015, with SIPO filings overwhelmingly dominating the sample (6.618 patents out of 8.807). The literature argues that drivers of the huge increase in Chinese patents in almost any technology and not just remote sensing are strategic/political motives, rather than real innovations (e.g., EPO et al. 2022). Hence, we correct for this potential bias by imposing an additional restriction: we include Chinese patents into our dataset only if these patents have been filed at least at two authorities.

8 We aggregated the 24 patent authorities for which we have filings to what we call 'global regions': United States (US), WO (patents being filed directly at the World Intellectual Property Organization), Asia (including SIPO patents with family size of 2 and larger), Europe, and ROW (Rest Of World). See Appendix A.3 for a breakdown of the global regions by patent authorities.

9 We pay particular attention to 'polysemic' words, that is, terms carrying distinct meanings—for example, crop is a noun in the agriculture field but a verb in other domains, such as image cropping in computer graphics. We exclude polysemic words like 'forest', 'tree', or 'environment' from the term dynamic perspective since they may be either related to modern algorithms or the natural, technical or even urban environment. However, when applying STM, we are able to trace the importance of polysemic words via their embedding within topics and, for example, focusing on related topic dynamics.

10 The choice of K42 is dictated by the ease of elaboration and presentation of the results. We conduct robustness tests with K60 and K62 models, obtaining comparable results in terms of topics' clustering.

[11] Based on the PATSTAT variable: earliest_filing_year.
[12] Based on the PATSTAT variable: authority.
[13] Based on the PATSTAT variable: psn_sector.
[14] Here, the polysemic term 'forest' is related to the plants and not to algorithms.
[15] Technically speaking, we link topics based on their cosine similarity with the edge size representing the level of similarity between two topics. We also apply a minimum threshold for edges to be shown.

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Firms' Use of Temporary Employment and Permanent Workers' Concerns about Job Security: Evidence from German Linked Employer-Employee Data

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Abstract: This research note addresses the question of how permanent workers perceive their individual job security if their firm employs temporary workers with fixed-term contracts and temporary agency workers. One the one hand, the core-periphery hypothesis predicts that permanent workers should have fewer concerns about job security if the firm employs temporary workers to deal with demand fluctuations. On the other hand, a counteracting substitution effect might increase concerns about job security. Using linked employer-employee data and estimating regression models at the worker level with establishment fixed effects, evidence supports the core-periphery hypothesis for temporary agency work but not for fixed-term contracts.

Keywords: core-periphery hypothesis; fixed-term contracts; job security; linked employer-employee data; temporary agency work

JEL Classification: J23; J42; M51

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1. Introduction

Firms use temporary employment for several reasons. In addition to screening new employees (Booth et al. 2002; Boockmann and Hagen 2008), two of the most important reasons are gaining external flexibility in employment and saving labor costs, which have different consequences for the job security of permanent workers employed in the same firm as temporary workers. Whereas the flexibility argument is related to the core-periphery hypothesis, saving labor costs is related to the substitution of the permanent workforce by temporary workers.

In Germany, temporary employment mainly consists of fixed-term contracts (FTC) and temporary agency work (TAW). FTCs are direct employment relationships with an employer. The abuse of consecutive FTCs is restricted by law to explicitly avoid a substitution of regular employment. FTCs without an objective reason are only allowed for up to 24 months for newly hired employees, with up to three renewals within these 24 months. If the FTC is justified by an objective reason (e.g., education) or conducted with specific employee groups (e.g., top managers, older unemployed), these restrictions do not apply. Moreover, FTCs cannot be terminated before the expiration date, otherwise severe firing costs occur (Cahuc et al. 2016). In contrast, TAW is indirect employment via agencies, which are the actual employers and are fully responsible for the employer-side obligations (e.g., payment, vacation, employment protection). In return, the agencies receive fees for sending the workers to other firms. These lending firms have a high degree of flexibility for which they pay the agencies, as they could lend workers even on a daily basis. The regulation of TAW is largely concerned with restrictions on the lending periods as well as the synchronization of lending and employment contracts. Such synchronization means that workers would only have an employment contract with the agency as long as they are sent to a lending firm, which would transfer employment risks from the agency to the workers.

The core-periphery hypothesis postulates that firms recruit temporary workers in times of increasing temporary labor demand and release them in times of decreasing demand. These temporary workers (periphery) are employed in addition to the permanent workforce (core) and serve as a buffer in an internal dual labor market, from which permanent workers gain job security (Rebitzer and Taylor 1991; Saint-Paul 1991; Booth et al. 2003; Cappelli and Neumark 2004; Pfeifer 2009). Thus, permanent workers should have fewer concerns about their job security if their firm uses temporary workers and if the share of temporary workers increases in their firm. Because TAW can be used more flexibly than FTCs, this effect should be more pronounced for TAW than for FTCs.

Contrarily, firms might recruit temporary workers to substitute permanent workers to save labor costs and might even keep them in times of a recession if the gap in labor costs between temporary and permanent workers is large enough (Koutentakis 2008; Cahuc et al. 2016). Thus, permanent workers should have more concerns about their job security if their firm uses temporary workers and if the share of temporary workers increases in their firm. Because firms must pay for the wages of TAW as well as the fees to the agencies, cost saving is more likely with the employment of workers with FTCs, so this substitution effect should be more pronounced for FTCs than for TAW.

We test these counteracting hypotheses by using linked employer-employee data and estimating regression models at the worker level with establishment fixed effects to deal with unobserved establishment heterogeneity. By using establishment fixed effects, we also explicitly account for the within-firm perspective of internal labor markets. We use the years 2012, 2014, 2016, and 2018 of the German Linked Personnel Panel (LPP). The uniqueness of these data is that we merge establishment surveys, which include information about the shares of FTCs and TAW, with worker surveys, which include information about permanent workers' perceived job security. As far as we know, we are the first to analyze the correlation between establishments' use of FTC and TAW and the perception of individual job security by permanent workers, for which linked employer-employee data are necessary. Whereas administrative linked employer-employee data with objective wage information and basic firm and worker characteristics have been widely used over the last two decades, empirical work using data that combine establishment surveys with worker surveys is still scarce.

The remainder of this research note is organized as follows. In the next section, we give a short overview of the legal arrangements of FTCs and TAW in Germany. It is followed by a section with information about the data, variables, and estimation approach of the study. We then report and discuss our estimation results. The paper concludes with a short summary and discussion of the main findings.

2. Overview of Temporary Employment Regulation in Germany

Fixed-term contracts (FTCs) in Germany were highly regulated until the introduction of the Employment Promotion Act ("Beschäftigungsförderungsgesetz") in 1985. This legal change relaxed the former rule that the employer had to demonstrate the temporary nature of the work (by providing objective reasons such as seasonal fluctuations) and that FTCs had a maximum duration of only six months. The Employment Promotion Act of 1985 allowed a single FTC to last up to 18 months without justification if the employee was newly hired or if an apprentice could not be offered a regular job. In 1996, the duration of FTCs was raised to 24 months, with three renewals possible within this period. Moreover, employees could be employed unconditionally under FTCs after finishing their apprenticeship. FTCs for employees older than 60 years were allowed without any restrictions on the duration. Finally, if the FTC was justified by an objective reason, the aforementioned restrictions did not apply. In January 2001, the regulation of FTCs in Germany was again renewed and regulated in a single law ("Gesetz über Teilzeitarbeit und befristete Arbeitsverträge"). One change affected the definition of the elderly: they were defined as older than 58 years instead of 60 years, because of the high unemployment rates among older workers. Already in 2002, a couple of further changes were introduced ("Erstes Gesetz für moderne Dienstleistungen am Arbeitsmarkt") including the prohibition of discrimination at the workplace, which refers to equal pay and treatment, and the definition of the elderly as older than 52 years. Since 2007, FTCs without restrictions on the duration need to be justified by an objective reason for older workers as is the case for younger workers, and for FTCs without objective reasons renewals are possible within five years for older workers. Note that FTCs cannot be terminated within the contract duration without severe firing costs, which makes them less flexible in the short run than permanent contracts.

In the year 1967, the federal constitutional court repealed the employment agency monopoly of the Federal Labor Office ("*Bundesanstalt für Arbeit*"), which led to the regulation of temporary agency work (TAW) in 1972 ("*Arbeitnehmerüberlassungsgesetz*"). The essence of this regulation, which is the full responsibility of the agency in all employer-side features (e.g., payments, employment protection), is still valid today. The general logic is that a worker has a labor contract with the agency, which has a contract with the lending firm in which the worker performs tasks. Several legal changes and the new legislations since 2002 (e.g., "*Job-Aqtiv-Gesetz*", "*Erstes Gesetz für moderne Dienstleistungen am Arbeitsmarkt*") have repealed restrictions on the lending periods as well as synchronization and have introduced equal pay and treatment for TAW in a lending firm. For example, the general lending period was increased from 3 months to 6 months (1985) to 9 months (1994) to 12 months (1997) to 24 months (2002) and was reduced to 18 months in 2017. Since 2017, the principle of equal pay and treatment already applies after 9 months. Note, however, that exemptions can be arranged in collective contracts.

3. Data and Estimation Approach

We use the years 2012, 2014, 2016, and 2018 of the German Linked Personnel Panel (LPP), which consists of linked questionnaires for employees and employers (Kampkötter et al. 2016; Mackeben et al. 2021). The employee questionnaire asks about job characteristics (including perceived job security), attitudes, personality, socio-demographic background, etc. The employer questionnaires, answered by the owners or top managers of the establishment, entail questions about the employment structure (including the share of FTCs and TAW), human resource management practices, general firm policies, industrial relations, etc. Note that the LPP is a representative subsample of the IAB Establishment Panel, but not of all German firms. While the IAB Establishment Panel focuses more on general management and employment structure issues, the LPP establishment survey focuses more on human resource management policies. Hence, our data entail information from the IAB Establishment Panel survey and from the LPP survey for employers. In more detail, the LPP is a sample of private sector establishments with 50 or more employees in manufacturing and service industries. The establishment sample is stratified according to four establishment size classes (50–99, 100–249, 250–499, and 500 and more employees), five industries (metalworking and electronic industries, further manufacturing industries, retail and transport, services for firms, and information and communication services), and four regions (North, East, South, and West).

After drawing the sample of establishments in a first step, a sample of employees within those establishments has been drawn in a second step. Thus, the stratification of the data is at the establishment level, not at the employee level. Nevertheless, we can perform our analysis based on the employee level using data from LPP employee surveys which we augmented with establishment level characteristics (LPP/IAB Establishment Panel). In more detail, the sampling of employees was conditioned on all employees working in the participating establishments on December 30th in the preceding year; employees were then randomly drawn and contacted via telephone interview. Note also that the establishment data are set up as an unbalanced panel, but not the employee data. Because we are interested in the relationship of the use and the employment share of FTCs and TAW to permanent workers' perceived job security, we restrict our sample to workers aged

18 to 65 years, who are in permanent employment with tenure of at least 18 months, which constitute more than 95 percent of observations in the total sample.

Our dependent variable for a worker's perceived job security has three ordinal outcomes, which are (1) not concerned at all (65%), (2) somewhat concerned (29%), and (3) very concerned (6%) about own job security. Additionally, we dichotomize the dependent variable to (0) no concerns and (1) low/high concerns about own job security. For both dependent variables, we estimate ordinary least squares (OLS) linear regressions with establishment fixed effects. Because of the ordinal and binary characters of our dependent variables, we additionally estimate ordered probit and binary probit models with establishment fixed effects as robustness checks. The basic regression equation looks as in equation (1), which is estimated for worker i in establishment j in year t. α denotes the constant. β's are the estimated coefficients for our explanatory variables of interests. γ's are the coefficients for the set of control variables X. μ_t denotes time fixed effects. ν_j denotes the establishment fixed effects. ε_{ijt} is the idiosyncratic error term of worker i in establishment j in year t.

$$JobSecurity_{ijt} = \alpha + \beta_1 FTCdummy_{ijt} + \beta_2 FTCshare_{ijt} + \beta_3 TAWdummy_{ijt} + \beta_4 TAWshare_{ijt} + \gamma X_{ijt} + \mu_t + \nu_j + \varepsilon_{ijt} \quad (1)$$

The explanatory variables of interest are at first the use of FTCs and TAW, which are specified as two dummy variables taking the value one if an establishment uses FTCs and TAW and the value zero if FTCs and TAW are not used. Moreover, we are interested in the intensity of FTCs and TAW, so we include the shares of FTCs and TAW in total employment at the establishment level. We estimate three specifications. The first specification includes dummies indicating if the establishment in which the permanent worker is employed uses FTCs and TAW in a given year. The second specification includes the employment shares of FTCs and TAW in a given year. The third specification combines the dummies and shares. Even though FTCs and TAW are establishment characteristics, their means are computed for workers employed in these establishments (see Table 1 for descriptive statistics). About 86 percent of workers are employed in establishments that use FTCs, with an average FTC employment share of 5.6 percent. About 67 percent of workers are employed in establishments that use TAW, with an average TAW employment share of 4.1 percent.

We control for a wide range of differences in socio-demographic characteristics (age, education, sex, having a partner, having children), personality based on multi-item scales (Big Five, trust), individual employment and job characteristics (labor income, working hours, managerial responsibilities, out-of-hours demand, decision autonomy, task autonomy, interdependence with co-workers, physical loading), some time-varying establishment characteristics (profit situation, workforce composition, establishment size categories), and the survey years (time fixed effects). Table 1 provides an overview and the descriptive statistics of the used variables. Additionally, we include establishment fixed effects in all regressions that control for time-invariant establishment characteristics (e.g., sector, region), because unobserved idiosyncratic factors at the establishment level can influence the potential to use temporary workers as well as workers' perceptions of individual job security (e.g., specific production technology, complementary HRM practices, necessary skills, incentive structures, competition, norms). Note also that we treat works councils, collective agreements, etc. as quasi time-invariant and argue that their potential impact is included in the establishment fixed effects, because status changes within the establishments are a very rare event. Thus, we estimate regressions at the worker level and include dummies for the establishments as establishment fixed effects. The variation of establishment characteristics such as the share of FTCs and TAW stems from the observation of establishments over the four-year unbalanced establishment panel, in which we only include establishments that are observed for at least two years. Moreover, we only use worker observations, if within-establishment variance exists for both dependent variables. In total, our estimation sample contains 12,288 observations of workers nested in 637 establishments.

Table 1. Descriptive statistics.

	Mean	Std. Dev.	Min	Max
Job security concerns categories (increasing)	1.406	0.595	1	3
Job security concerns dummy (no vs. low/high)	0.349		0	1
FTC dummy	0.860		0	1
TAW dummy	0.667		0	1
FTC share	0.056	0.086	0	0.974
TAW share	0.041	0.074	0	0.939
Monthly net salary in thousand Euros	2.456	2.284	0.001	170.000
Age in years	44.345	10.303	18	65
Male	0.749		0	1
Having partner	0.848		0	1
Number of children < 14 years	0.389	0.749	0	5
University degree	0.256		0	1
German citizenship	0.979		0	1
Number of actual weekly working hours	40.582	8.575	0.500	90.000
Management position	0.295		0	1
Available outside working time (increasing)	2.041	1.126	1	5
Decision autonomy (increasing)	3.971	0.993	1	5
Task variety (increasing)	4.179	0.948	1	5
Dependence on co-worker (increasing)	3.761	1.219	1	5
Co-worker depend on me (increasing)	3.351	1.268	1	5
Physical work environment (increasing)	2.291	1.429	1	5
Agreeableness (increasing)	4.047	0.573	1	5
Consciousness (increasing)	4.355	0.481	1.667	5
Neuroticism (increasing)	2.698	0.768	1	5
Openness (increasing)	3.637	0.630	1	5
Extraversion (increasing)	3.654	0.737	1	5
Trust (increasing)	3.504	0.784	1	5
Profit situation categories (increasing)	3.528	0.967	1	5
Share female employees	0.264	0.203	0	0.985
Share high skilled employees	0.139	0.147	0	0.875
Share medium skilled employees	0.656	0.213	0	1
Establishment size dummies				
50–99 regular employees	0.110		0	1
100–249 regular employees	0.231		0	1
250–499 regular employees	0.246		0	1
>499 regular employees	0.407		0	1
Year dummies				
2012	0.291		0	1
2014	0.304		0	1
2016	0.231		0	1
2018	0.174		0	1

Notes: Number of worker-year observations is 12,288 nested in 637 establishments. Standard deviations for dummy variables are not displayed. Data: LPP 2012, 2014, 2016, and 2018.

4. Regression Results

We have estimated three specifications for the ordinal as well as for the binary dependent variables. The first specification includes dummies indicating if the establishment in which the permanent worker is employed uses FTCs and TAW in a given year. The second specification includes the employment share of FTCs and TAW in a given year. The third specification combines both. The OLS as well as the ordered and binary probit regression results for our main explanatory variables of interest (use and share of FTCs and TAW) in Table 2 show robust findings across all specifications and regression techniques. First, the use and the share of FTCs are correlated with more concerns about permanent workers' own job security. However, the coefficients are not statistically significant in any specification. Thus, permanent workers do not have on average a significantly higher probability of having concerns about their own job security if their firm uses FTCs. It should also be noted, however, that permanent workers do not have a lower probability of having concerns about job security if their firm uses FTCs. Hence, our findings for FTCs give neither support for the substitution hypothesis (more concerns about job security among permanent workers) nor the core-periphery hypothesis (fewer concerns about job security among permanent workers).

Table 2. Summary of regression results for permanent workers' concerns about own job security.

	Ordinal Concerns (OLS)			Binary Concerns (OLS)		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
FTC dummy	0.0229		0.0162	0.0184		0.0157
	(0.364)		(0.535)	(0.351)		(0.441)
	[0.025]		[0.026]	[0.020]		[0.020]
FTC share		0.1993	0.1724		0.0901	0.0644
		(0.290)	(0.382)		(0.513)	(0.655)
		[0.188]	[0.197]		[0.138]	[0.144]
TAW dummy	−0.0355		−0.0226	−0.0296		−0.0190
	(0.164)		(0.384)	(0.178)		(0.394)
	[0.026]		[0.026]	[0.022]		[0.022]
TAW share		−0.3389 **	−0.3031 **		−0.2825 **	−0.2522 **
		(0.026)	(0.049)		(0.022)	(0.045)
		[0.151]	[0.154]		[0.123]	[0.123]
All control variables + establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.219	0.220	0.220	0.191	0.191	0.191
Adjusted R squared	0.174	0.175	0.175	0.144	0.145	0.145
Mean dep. var.	1.406	1.406	1.406	0.349	0.349	0.349
	Ordinal Concerns (Ordered Probit)			**Binary Concerns (Binary Probit)**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
FTC dummy	0.0450		0.0304	0.0567		0.0482
	(0.386)		(0.570)	(0.308)		(0.400)
	[0.052]		[0.053]	[0.056]		[0.057]
FTC share		0.4198	0.3665		0.2921	0.2107
		(0.220)	(0.299)		(0.429)	(0.580)
		[0.343]	[0.353]		[0.369]	[0.380]
TAW dummy	−0.0790		−0.0506	−0.0916		−0.0602
	(0.133)		(0.353)	(0.105)		(0.303)
	[0.053]		[0.055]	[0.056]		[0.058]
TAW share		−0.6894 **	−0.6062 *		−0.8156 **	−0.7219 **
		(0.026)	(0.059)		(0.015)	(0.037)
		[0.310]	[0.322]		[0.335]	[0.346]
All control variables + establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R squared	0.147	0.147	0.147	0.161	0.161	0.161

Notes: OLS coefficients with p-values for clustered standard errors at the establishment level in parentheses and clustered standard errors at the establishment level in squared brackets. Ordered and binary probit coefficients with p-values in parentheses and standard errors in squared brackets. ** $p < 0.05$, * $p < 0.10$. Number of worker-year observations is 12,288 nested in 637 establishments in all regressions. Complete results are displayed in Table 3 for the OLS regressions and in Table 4 for the ordered and binary probit regressions. Data: LPP 2012, 2014, 2016, and 2018.

Table 3. Complete OLS regression results.

	Job Security Concerns Ordered Categories (OLS)			Job Security Concerns Dummy (OLS)		
	(1)	(2)	(3)	(1)	(2)	(3)
FTC dummy	0.0229		0.0162	0.0184		0.0157
	(0.364)		(0.535)	(0.351)		(0.441)
TAW dummy	−0.0355		−0.0226	−0.0296		−0.0190
	(0.164)		(0.384)	(0.178)		(0.394)
FTC share		0.1993	0.1724		0.0901	0.0644
		(0.290)	(0.382)		(0.513)	(0.655)
TAW share		−0.3389 **	−0.3031 **		−0.2825 **	−0.2522 **
		(0.026)	(0.049)		(0.022)	(0.045)
Monthly net salary in thousand Euros	−0.0006	−0.0007	−0.0006	−0.0019	−0.0020	−0.0019
	(0.888)	(0.873)	(0.892)	(0.424)	(0.408)	(0.435)
Age in years	0.0002	0.0002	0.0002	−0.0005	−0.0005	−0.0005
	(0.751)	(0.748)	(0.747)	(0.434)	(0.434)	(0.434)
Male	−0.0321 *	−0.0321 *	−0.0321 *	−0.0271 *	−0.0271 *	−0.0271 *
	(0.080)	(0.080)	(0.079)	(0.072)	(0.072)	(0.071)
Having partner	−0.0140	−0.0142	−0.0143	0.0055	0.0053	0.0053
	(0.391)	(0.382)	(0.382)	(0.657)	(0.667)	(0.668)
Number of children < 14 years	0.0279 ***	0.0278 ***	0.0279 ***	0.0189 ***	0.0187 ***	0.0188 ***
	(0.002)	(0.002)	(0.002)	(0.008)	(0.008)	(0.008)
University degree	0.0092	0.0089	0.0087	0.0020	0.0018	0.0016
	(0.513)	(0.527)	(0.535)	(0.861)	(0.875)	(0.886)
German citizenship	−0.0543	−0.0537	−0.0536	−0.0247	−0.0244	−0.0243
	(0.235)	(0.240)	(0.240)	(0.460)	(0.466)	(0.467)
Number of actual weekly working hours	0.0004	0.0004	0.0004	−0.0001	−0.0001	−0.0001
	(0.584)	(0.592)	(0.592)	(0.877)	(0.863)	(0.863)
Management position	−0.0136	−0.0137	−0.0134	−0.0060	−0.0060	−0.0059
	(0.335)	(0.334)	(0.341)	(0.608)	(0.609)	(0.619)
Available outside working time (increasing)	0.0144 **	0.0144 **	0.0144 **	0.0140 ***	0.0140 ***	0.0140 ***
	(0.025)	(0.025)	(0.025)	(0.005)	(0.005)	(0.005)
Decision autonomy (increasing)	−0.0484 ***	−0.0482 ***	−0.0483 ***	−0.0360 ***	−0.0358 ***	−0.0359 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Task variety (increasing)	−0.0017	−0.0018	−0.0017	−0.0041	−0.0042	−0.0041
	(0.796)	(0.783)	(0.792)	(0.424)	(0.411)	(0.418)
Dependence on co-worker (increasing)	0.0072	0.0072	0.0072	0.0037	0.0037	0.0037
	(0.126)	(0.125)	(0.123)	(0.315)	(0.308)	(0.304)
Co-worker depend on me (increasing)	0.0189 ***	0.0189 ***	0.0189 ***	0.0133 ***	0.0134 ***	0.0133 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Physical work environment (increasing)	0.0280 ***	0.0280 ***	0.0280 ***	0.0188 ***	0.0187 ***	0.0187 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Agreeableness (increasing)	0.0084	0.0084	0.0084	0.0042	0.0042	0.0042
	(0.465)	(0.464)	(0.464)	(0.656)	(0.654)	(0.654)
Consciousness (increasing)	0.0072	0.0073	0.0073	0.0017	0.0018	0.0017
	(0.598)	(0.595)	(0.595)	(0.882)	(0.877)	(0.879)
Neuroticism (increasing)	0.1194 ***	0.1191 ***	0.1192 ***	0.0910 ***	0.0908 ***	0.0908 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Openness (increasing)	0.0046	0.0044	0.0045	−0.0034	−0.0035	−0.0034
	(0.658)	(0.669)	(0.660)	(0.678)	(0.668)	(0.679)
Extraversion (increasing)	−0.0256 ***	−0.0256 ***	−0.0256 ***	−0.0293 ***	−0.0293 ***	−0.0294 ***
	(0.004)	(0.004)	(0.004)	(<0.001)	(<0.001)	(<0.001)
Trust (increasing)	−0.0524 ***	−0.0524 ***	−0.0524 ***	−0.0348 ***	−0.0348 ***	−0.0348 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Profit situation categories (increasing)	−0.0284 **	−0.0293 **	−0.0285 **	−0.0180 *	−0.0186 **	−0.0178 *
	(0.023)	(0.020)	(0.023)	(0.052)	(0.049)	(0.055)

Table 3. *Cont.*

	Job Security Concerns Ordered Categories (OLS)			Job Security Concerns Dummy (OLS)		
	(1)	(2)	(3)	(1)	(2)	(3)
Share female employees	−0.0941	−0.1002	−0.0947	0.0042	−0.0012	0.0032
	(0.567)	(0.540)	(0.562)	(0.972)	(0.992)	(0.979)
Share high skilled employees	0.1333	0.1329	0.1393	0.1662	0.1632	0.1693
	(0.520)	(0.513)	(0.496)	(0.288)	(0.287)	(0.274)
Share medium skilled employees	−0.0692	−0.0642	−0.0656	0.0136	0.0176	0.0164
	(0.384)	(0.416)	(0.405)	(0.809)	(0.754)	(0.770)
Establishment size dummies (ref. <50)						
50–99 regular employees	0.4352 ***	0.4284 ***	0.4310 ***	0.2474 ***	0.2399 ***	0.2425 ***
	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.001)	(0.001)
100–249 regular employees	0.4874 ***	0.4803 ***	0.4814 ***	0.2888 ***	0.2815 ***	0.2827 ***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
250–499 regular employees	0.5562 ***	0.5430 ***	0.5432 ***	0.3416 ***	0.3293 ***	0.3298 ***
	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.001)	(0.001)
>499 regular employees	0.6926 ***	0.6801 ***	0.6809 ***	0.4568 ***	0.4452 ***	0.4461 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Year dummies (ref. 2012)						
2014	−0.0533 ***	−0.0547 ***	−0.0543 ***	−0.0444 ***	−0.0459 ***	−0.0455 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(<0.001)	(0.001)
2016	−0.0549 ***	−0.0571 ***	−0.0564 ***	−0.0485 ***	−0.0509 ***	−0.0503 ***
	(0.007)	(0.005)	(0.005)	(0.003)	(0.002)	(0.002)
2018	0.0167	0.0135	0.0151	0.0107	0.0077	0.0091
	(0.617)	(0.683)	(0.650)	(0.707)	(0.783)	(0.745)
Establishment fixed effects (637)	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.9513 ***	0.9642 ***	0.9590 ***	0.1064	0.1225	0.1162
	(<0.001)	(<0.001)	(<0.001)	(0.427)	(0.353)	(0.384)
Number of observations	12,288	12,288	12,288	12,288	12,288	12,288
R-squared	0.219	0.220	0.220	0.191	0.191	0.191
Adjusted R-squared	0.174	0.175	0.175	0.144	0.145	0.145

Notes: OLS coefficients with p-values for clustered standard errors at the establishment level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Number of worker-year observations is 12,288 nested in 637 establishments. Data: LPP 2012, 2014, 2016, and 2018.

Second, the use and the share of TAW are correlated with fewer concerns about the job security of permanent workers. Whereas the use of TAW is statistically significant between the 10 and 18 percent level only in the first specifications, the share of TAW is statistically significant at least at the 6 percent level in all specifications. We provide a simple quantitative interpretation based on the coefficients of specification three of the OLS regressions for the binary dependent concern variable (last column in the upper part of Table 2), which has a mean of 0.35, i.e., 35 percent of permanent workers in our sample have low or high concerns, and 65 percent have no concerns about their own job security. The use of TAW in an establishment reduces the probability of having (low or high) concerns about job security among permanent workers by about two percentage points. A one percentage point higher share of TAW in the establishment reduces the probability of having (low or high) concerns about the own job security among permanent workers by additional 0.25 percentage points. Thus, permanent workers in a firm with a 10 percent TAW share would have on average a 4.4 percentage point ($-0.0190 - 0.1 \times 0.2522 = -0.04422$) lower probability of having concerns about their own job security compared to the situation in which the firm does not use TAW. Hence, our findings for TAW give on average more support to the core-periphery hypothesis than for the substitution hypothesis, i.e., core employees with permanent employment contracts benefit if firms can use TAW.

Table 4. Complete ordered and binary probit regression results.

	Job Security Concerns Categories (Ordered Probit)			Job Security Concerns Dummy (Binary Probit)		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
FTC dummy	0.0450		0.0304	0.0567		0.0482
	(0.386)		(0.570)	(0.308)		(0.400)
TAW dummy	−0.0790		−0.0506	−0.0916		−0.0602
	(0.133)		(0.353)	(0.105)		(0.303)
FTC share		0.4198	0.3665		0.2921	0.2107
		(0.220)	(0.299)		(0.429)	(0.580)
TAW share		−0.6894 **	−0.6062 *		−0.8156 **	−0.7219 **
		(0.026)	(0.059)		(0.015)	(0.037)
Monthly net salary in thousand Euros	−0.0021	−0.0022	−0.0020	−0.0063	−0.0065	−0.0062
	(0.692)	(0.667)	(0.695)	(0.269)	(0.254)	(0.275)
Age in years	0.0002	0.0002	0.0002	−0.0014	−0.0013	−0.0014
	(0.864)	(0.857)	(0.858)	(0.350)	(0.354)	(0.352)
Male	−0.0829 **	−0.0832 **	−0.0831 **	−0.0879 **	−0.0879 **	−0.0879 **
	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
Having partner	−0.0173	−0.0179	−0.0179	0.0246	0.0242	0.0242
	(0.633)	(0.622)	(0.623)	(0.527)	(0.535)	(0.535)
Number of children < 14 years	0.0687 ***	0.0684 ***	0.0686 ***	0.0617 ***	0.0612 ***	0.0614 ***
	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.001)	(0.001)
University degree	0.0232	0.0229	0.0226	0.0071	0.0068	0.0063
	(0.456)	(0.461)	(0.468)	(0.829)	(0.836)	(0.850)
German citizenship	−0.1069	−0.1062	−0.1057	−0.0808	−0.0798	−0.0794
	(0.196)	(0.199)	(0.201)	(0.369)	(0.375)	(0.377)
Number of actual weekly working hours	0.0007	0.0007	0.0007	−0.0004	−0.0004	−0.0004
	(0.682)	(0.673)	(0.675)	(0.836)	(0.836)	(0.833)
Management position	−0.0388	−0.0393	−0.0388	−0.0262	−0.0266	−0.0261
	(0.208)	(0.203)	(0.208)	(0.424)	(0.416)	(0.426)
Available outside working time (increasing)	0.0409 ***	0.0408 ***	0.0408 ***	0.0480 ***	0.0481 ***	0.0480 ***
	(0.002)	(0.002)	(0.002)	(<0.001)	(<0.001)	(<0.001)
Decision autonomy (increasing)	−0.1144 ***	−0.1140 ***	−0.1143 ***	−0.1133 ***	−0.1127 ***	−0.1131 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Task variety (increasing)	−0.0090	−0.0094	−0.0092	−0.0145	−0.0150	−0.0147
	(0.521)	(0.502)	(0.513)	(0.334)	(0.318)	(0.328)
Dependence on co-worker (increasing)	0.0173	0.0175	0.0176	0.0126	0.0128	0.0129
	(0.123)	(0.117)	(0.117)	(0.291)	(0.284)	(0.279)
Co-worker depend on me (increasing)	0.0488 ***	0.0488 ***	0.0488 ***	0.0446 ***	0.0447 ***	0.0447 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Physical work environment (increasing)	0.0684 ***	0.0681 ***	0.0681 ***	0.0610 ***	0.0608 ***	0.0609 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Agreeableness (increasing)	0.0165	0.0167	0.0167	0.0141	0.0143	0.0142
	(0.474)	(0.468)	(0.468)	(0.565)	(0.561)	(0.563)
Consciousness (increasing)	0.0097	0.0099	0.0100	0.0002	0.0006	0.0005
	(0.733)	(0.728)	(0.727)	(0.994)	(0.984)	(0.986)
Neuroticism (increasing)	0.2962 ***	0.2958 ***	0.2960 ***	0.2927 ***	0.2921 ***	0.2923 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Openness (increasing)	0.0060	0.0055	0.0058	−0.0146	−0.0150	−0.0146
	(0.780)	(0.800)	(0.789)	(0.527)	(0.515)	(0.526)
Extraversion (increasing)	−0.0691 ***	−0.0690 ***	−0.0690 ***	−0.0973 ***	−0.0975 ***	−0.0976 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Trust (increasing)	−0.1253 ***	−0.1254 ***	−0.1254 ***	−0.1108 ***	−0.1109 ***	−0.1109 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Profit situation categories (increasing)	−0.0650 ***	−0.0674 ***	−0.0656 ***	−0.0558 **	−0.0578 ***	−0.0554 **
	(0.002)	(0.001)	(0.002)	(0.012)	(0.009)	(0.013)

Table 4. *Cont.*

	Job Security Concerns Categories (Ordered Probit)			Job Security Concerns Dummy (Binary Probit)		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Share female employees	−0.3091	−0.3266	−0.3103	−0.0398	−0.0586	−0.0401
	(0.404)	(0.377)	(0.402)	(0.921)	(0.883)	(0.920)
Share high skilled employees	0.3481	0.3534	0.3661	0.4787	0.4734	0.4902
	(0.329)	(0.322)	(0.305)	(0.217)	(0.222)	(0.206)
Share medium skilled employees	−0.1376	−0.1247	−0.1293	0.0505	0.0645	0.0587
	(0.404)	(0.449)	(0.433)	(0.777)	(0.717)	(0.742)
Establishment size dummies (ref. <50)						
50–99 regular employees	0.8935 ***	0.8724 ***	0.8787 ***	0.7776 ***	0.7507 ***	0.7604 ***
	(<0.001)	(<0.001)	(<0.001)	(0.003)	(0.004)	(0.003)
100–249 regular employees	1.0096 ***	0.9859 ***	0.9890 ***	0.9005 ***	0.8707 ***	0.8764 ***
	(<0.001)	(<0.001)	(<0.001)	(0.002)	(0.003)	(0.003)
250–499 regular employees	1.1619 ***	1.1234 ***	1.1239 ***	1.0499 ***	1.0046 ***	1.0071 ***
	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.002)	(0.002)
>499 regular employees	1.4654 ***	1.4264 ***	1.4289 ***	1.3974 ***	1.3521 ***	1.3568 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Year dummies (ref. 2012)						
2014	−0.1323 ***	−0.1353 ***	−0.1341 ***	−0.1441 ***	−0.1484 ***	−0.1473 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
2016	−0.1398 ***	−0.1437 ***	−0.1418 ***	−0.1615 ***	−0.1681 ***	−0.1661 ***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
2018	0.0439	0.0385	0.0418	0.0344	0.0264	0.0304
	(0.327)	(0.391)	(0.353)	(0.471)	(0.581)	(0.525)
Establishment fixed effects (637)	Yes	Yes	Yes	Yes	Yes	Yes
Cut point 1	1.9138	1.9038	1.8971			
Cut point 2	3.3639	3.3544	3.3478			
Constant				−1.7443	−1.7240	−1.7296
Number of observations	12,288	12,288	12,288	12,288	12,288	12,288
Pseudo R-squared	0.147	0.147	0.147	0.161	0.161	0.161

Notes: Ordered and binary probit coefficients with p-values in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Number of worker-year observations is 12,288 nested in 637 establishments. Data: LPP 2012, 2014, 2016, and 2018.

Finally, we look at significant coefficients estimated for our control variables. Table 3 contains the complete results for the OLS regressions, and Table 4 contains those for the ordered and binary probit regressions. A comparison of the different specifications with ordinal and binary dependent variables for own job concerns as well as a comparison of the estimates using OLS and probit regressions do not reveal noteworthy differences, so we give an overall interpretation. The results for the socio-demographic control variables reveal that men have on average fewer concerns about their own job security than women and that workers with children younger than 14 years have on average more concerns about their own job security. Note that the estimated coefficients for the number of young children contain the probability (having young children at all) as well the number of young children. One reason why parents have more concerns about job security might be that a job loss affects not only oneself but the entire family. Moreover, our results indicate that job-related characteristics are important. Workers with higher decision autonomy in a firm are less concerned about their own job security. However, workers have more concerns about their job security if they state a higher availability outside regular working time, a higher dependence of co-workers on oneself, and a more physical work environment. Some personality characteristics of workers are also significantly correlated with concerns about job security, which stresses their importance as control variables. Whereas workers with higher levels of neuroticism report more concerns about job security, workers with higher levels of extraversion and trust report fewer concerns. Although we have included establishment fixed effects, results for time varying establishment characteristics show that workers in larger firms and in firms with a better profit situation have on average fewer concerns about job security. Due to the inclusion of establishment fixed effects (within instead of between perspective) both results can be plausibly interpreted in the way that job security is larger if firms increase employment and improve their profit situation.

5. Concluding Remarks

Cappelli and Neumark (2004, p. 177) have analyzed turnover rates in a cross-section of establishments in the US and concluded: "*the evidence paints a rather clear picture regarding the core-periphery hypothesis because we find that contingent work [use of any contract, leased, or temporary agency workers (page 158)] and involuntary turnover of the permanent workforce are positively and significantly related, contradicting the core-periphery hypothesis*". However, their correlations between turnover rates and the use of temporary employment might be driven by unobserved factors at the establishment level, which we consider by the inclusion of establishment fixed effects in our regressions. Moreover, involuntary turnover rates at the establishment level are only one implication of the core-periphery hypothesis. More central to the core-periphery hypothesis is the question of how permanent workers perceive their job security, because this also affects the willingness to accept compensating wage differentials and to stay in the establishment.

Our results support the core-periphery hypothesis for TAW, i.e., permanent workers perceive their job security as larger when firms use TAW. We find, however, no evidence for the core-periphery hypothesis for FTCs. However, the non-significant estimates for FTCs also indicate that substitution is not that pronounced, as is indeed intended by German labor law, which restricts consecutive FTCs. Although the permanent (core) workforce might benefit by using an additional temporary (peripheral) workforce in internal dual labor markets, an overall welfare perspective would need to include an additional assessment if temporary jobs are stepping-stones for better permanent jobs or if temporary workers are stuck in dead-end jobs with low job security, low pay, and few career advancement opportunities (Booth et al. 2002; Jahn and Rosholm 2014).

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Flexible Use of the Large-Scale Short-Time Work Scheme in Germany during the Pandemic: Dynamic Labour Demand Models Estimation with High-Frequency Establishment Data

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Abstract: Our study uses 24 waves of the survey Establishments in the COVID-19 crisis (BeCOVID), a high-frequency dataset collected at monthly intervals by the Institute for Employment Research during the COVID-19 pandemic, to investigate the behaviour of establishments with respect to the dynamics of their employment, in particular their use of short-time work. Due to the high-frequency intervals, the present data are considerably better suited than annual panel surveys to investigate adjustment processes. This is especially true for the role of short-time work, which is seen as a particularly fast adjustment option and thus reduces adjustment costs rapidly. Our estimations reveal a much faster overall workforce adjustment process compared with previous studies, which rely on annual panel surveys. In addition, our empirical results show that the employment adjustment in establishments using short-time work during the COVID-19 crisis occurred almost immediately within one month.

Keywords: short-time work; COVID-19; dynamic labour demand; panel analysis; high-frequency establishment data

JEL Classification: C23; C26; J23; J39

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1. Introduction

During the COVID-19 pandemic, many countries used income and job-preserving measures, including short-time work (STW) schemes, in supporting workers' income and ensuring that employment rapidly rebounded as COVID-19 'crisis-related' shutdowns were erased (OECD 2020). The adoption of job retention schemes reached an all-time high in the OECD countries in the pandemic, with 60 million jobs preserved—more than 10 times as many as during the Great Recession 2008/2009 (OECD 2021, 2022). As the use of STW is expensive, needs appropriate agencies and can provide wrong incentives, measures adopted in other countries were wage subsidies, subsidies for periods of leave and bans on dismissals in times of crisis, as well as income transfers to employees and business aid programmes (Fitzenberger and Walwei 2023). However, international observers argue that STW programmes are effective in preserving existing jobs, but they may not be efficient in the reallocation of workers from unviable jobs to industries and firms with better prospects (International Monetary Fund 2020; OECD 2020). Furthermore, despite the experiences with the instrument of STW gained during the Great Recession 2008/2009, the massive programme has reached its administrative limits, particularly concerning the flexibility in the amount of work compensated for and the multi-stage application procedure (Fitzenberger and Walwei 2023). The pandemic provides an excellent example for this conflict. On the one hand, exceptional STW measures in response to the COVID-19 crisis in Germany, such as the increase of the eligibility threshold of affected workers and the coverage of 100% of social security contributions for the lost hours starting from the first month, made the STW scheme more attractive for both employers and employees. On the other hand, these adjustments of regulations provided additional incentives to lock-in employees in their current jobs and decrease their willingness to switch jobs. Although a huge bulk of the literature has been devoted to studying the effects of large-scale STW programmes on employment and unemployment (e.g., Mosley and Kruppe 1996; Hijzen and Venn 2011; Boeri and Bruecker 2011; Bellmann et al. 2013; Cahuc et al. 2018, 2021), analyses of the entries into and exits from firms and employees from this scheme are missing, especially applying microdata.

As the adoption of STW schemes varied over the course of the pandemic, annual employer and employee surveys cannot be used to investigate the entries and exits because establishments' representatives and employees are not able to remember the exact timing of the events and answer the questions reliably. As administrative data from, e.g., the Federal Employment Agency, do not include the complete relevant variables, surveys among the establishment representatives must be conducted. Using a unique establishment survey Establishments in the COVID-19 crisis (BeCOVID), which was launched by the Institute for Employment Research (Institut für Arbeitsmarkt-und Berufsforschung, IAB)—partially in cooperation with the Federal Institute for Occupational Safety and Health (Bundesanstalt für Arbeitsschutz und Arbeitsmedizin, BAuA) and the excellence cluster ECONtribute of the universities Cologne and Bonn—we study the impact of the pandemic on German establishments (Bellmann et al. 2022).

This paper contributes to the literature, firstly by investigating the effects of STW on the dynamics of employment during the pandemic, a time when STW schemes were adopted at an unprecedented level, not only in Germany. Secondly, we use 24 waves of Germany high-frequency establishment panel data in order to estimate, thirdly, a dynamic labour demand model using a two-stage general method of moments system estimator (Arellano and Bond 1991; Blundell and Bond 1998).

The remainder of the paper is structured as follows. Section 2 presents the institutional background related to the German STW scheme and the previous literature. Section 3 describes the dataset. In Section 4, our theoretical model and empirical strategy are outlined. Section 5 shows some descriptive statistics and the empirical model, and Section 6 presents the econometric results. Section 7 discusses the results and Section 8 briefly concludes.

2. Institutional Background and Previous Literature

The COVID-19 crisis severely affected the German economy from March 2020 onwards. In the second quarter of 2020, real GDP decreased by more than 10 percent and 5 percent over 2020, respectively; and, in the third quarter of 2021, real GDP increased by more than 8 percent (Destatis 2022). In February 2022, the Germany economy was hit by the war of aggression against Ukraine. GDP increased by 1.9 percent in 2022. In the light of Germany's successful reaction to the Great Recession, with a very limited increase of unemployment and decrease of employment but a subsequent growth in productivity and employment (Bellmann et al. 2016), STW became the blueprint for many countries during the COVID-19 crisis.

STW aims to reduce the labour costs of establishments facing a major drop in activity for economic reasons due to extraordinary events, if the drop is regarded as temporary and unavoidable (Konle-Seidl 2020; Fitzenberger and Walwei 2023). In normal times, the labour agency reimburses 60 percent of the last net earnings for a childless worker and 67 percent for a worker with children. Social security contributions for lost working hours usually have to be fully covered by the employer. Special regulations are valid for employees with a temporary contract and apprentices. So-called mini-jobbers, solo self-employed and new entrants to the labour market are not covered. STW can be paid for a maximum of 12 months. During the pandemic, some extensions of the STW scheme were enacted, including the following:

(1) The entitlement period was prolonged, so that the STW allowances could be paid for a maximum of 24 months.
(2) Social security contributions for the lost working hours were covered by the labour agency from the first month.
(3) The replacement rate was raised to 70 percent for employees without children and 77 percent for employees with children beginning in the fourth month of STW, and to 80 percent and 87 percent, respectively, from the seventh month.
(4) Employees with temporary contracts became eligible.

As several lockdowns were imposed, the incidence of STW varied considerably over time. In April 2020, the number of workers for whom their employers notified a shortage of work to the labour agency was approximately 10 million. However, the actual number of employees on STW schemes was approximately 6 million, i.e., 14% of the labour force. The relative number of employees with STW was highest in the accommodation and food services (Federal Employment Services 2022). Thus, due to the severity of the crisis, the attractiveness of STW was improved. To avoid the lock-in of employees, incentives were created to end individual STW episodes (Bellmann and Jenckel 2020; Fitzenberger and Walwei 2023):

(1) The extension of the period during which the STW allowance could be paid was from 12 months to up to 24 months ending 31 December 2021 at the latest only for those establishments that had introduced STW by 31 December 2020.
(2) Full reimbursement of social insurance contributions was possible until June 2021, followed by reimbursement of half of the amount until 31 December 2021.
(3) Increased STW allowance after the fourth and the seventh month, if the loss of work was at least 50 percent and STW had been introduced by 31 March 2021.
(4) Possibility of supplementary earnings, e.g., through part-time work, up to the normal pay level until 31 December 2021 (Bellmann et al. 2020).
(5) Skills development during STW was made more attractive for the employers.

These adjustments of the STW programme design helped to limit and decrease the number of participants, e.g., the BeCOVID survey reveals that in manufacturing the proportion of establishments using STW decreased from 40 percent in March–August to 34 percent in October, in trade and repair from 43 to 21 percent, and in hotels and restaurants from 63 to 35 percent (Bellmann and Jenckel 2020). Noteworthy, the OECD (2021) wrote in the executive summary of its Employment Outlook that job retention schemes helped to limit rises in unemployment while there is no indication that they had a significant adverse impact on job creation. As a number of countries started scaling back the level of STW, the burden of the COVID-19 crisis fell disproportionally on already vulnerable groups with the need to upskill and reskill the workforce (OECD 2022).

STW was used for the first time in the tobacco crisis in Baden in 1909, more intensively during the Great Depression and after World War II (Schmid 2022). A dramatic increase of unemployment after the German reunification was avoided by STW (Mosley et al. 1995). As already mentioned, the instrument was used on the initiative of the then minister of labour and social affairs, Olaf Scholz, during the Great Recession 2008/2009. Studies conducted by Boeri and Bruecker (2011), Scholz et al. (2011), Crimmann et al. (2012) and Bellmann et al. (2013) reveal that STW was successful in reducing job losses during the Great Recession, and was highly dynamic and well targeted. However, favourable pre-crisis conditions after government interventions, such as bailout packages, and pacts for employment and competitiveness, aided the positive employment development (Bellmann et al. 2016). Macroeconomic evaluation studies demonstrated that the existence of STW reduced fluctuations of both employment and output (Balleer et al. 2016).

3. Data

For our analyses, we use data from the survey "Establishments in the COVID-19 Crisis" (BeCOVID) (Backhaus et al. 2021; Fitzenbeger et al. 2021; Bellmann et al. 2022), a high-frequency rotating panel survey that started in August 2020 and ended in August

2022. It was conducted on behalf of the Institute for Employment Research (IAB) in order to monitor establishments during the COVID-19 crisis. The survey comprises twenty-four waves, each including between 1500 and 2000 establishments, representative for private sector establishments with at least one employer subject to social security contributions. The sampling frame was the establishment file of the Federal Employment Agency, which contains all establishments that have to submit employee notifications to the social security system. In the questionnaire, the respondents were asked to report not only socially insured employees but also civil servants, family workers and owners or proprietors. The sample was drawn via disproportionate sampling, stratified by establishments size (1–9, 10–49, 50–249 and 250+ employees) interacted with five broad economic sectors. Data collection was performed by Kantar Public and was carried out by computer-assisted telephone interviews (CATI). The definition and the measurement of variables of interest are provided in Table 1.

Table 1. Descriptive statistics of dependent and independent variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
Number of workers (log.)	45,852	3.289081	1.548164	0	11.35041
Average daily wage 2020 (log.)	39,670	4.531232	0.3603016	2.152924	6.67605
Share of unskilled workers	43,996	0.1448739	0.2092642	0	1
Number of short-time workers	42,463	4.585333	29.10596	0	2000
Short-time work (=1)	7382	0.172917	0.3781799	0	1
Supply of goods and services					
Exclusively or mainly within Germany	39,761	0.8807008	0.3241438	0	1
Mainly outside Germany	1360	0.0301238	0.1709299	0	1
In equal parts within and outside Germany	4026	0.0891754	0.2849999	0	1
Foreign ownership (=1)	2692	0.0591752	0.235955	0	1
Works council (=1)	9986	0.2179921	0.4128865	0	1
Liquidity (duration until insolvency)					
1 to 2 weeks	530	0.0130071	0.1133059	0	1
up to 4 weeks	1761	0.0432179	0.2033498	0	1
up to 2 months	5068	0.1243773	0.3300155	0	1
up to 6 months	7821	0.1919405	0.3938314	0	1
up to 12 months	3879	0.0951972	0.2934907	0	1
sufficient reserve	21,688	0.53226	0.4989643	0	1
Industry					
Agriculture, forestry and fishing	672	0.0136393	0.1159896	0	1
Mining and quarrying	56	0.0012182	0.0348816	0	1
Manufacturing industries	7881	0.1714379	0.3768953	0	1
Energy supply	124	0.0026974	0.0518671	0	1
Water supply	257	0.0055906	0.0745618	0	1
Construction	3718	0.0808788	0.2726519	0	1
Trade and maintenance	8671	0.188623	0.3912131	0	1
Transportation and storage	1733	0.0376985	0.1904681	0	1
Hospitality industry	2165	0.0470959	0.2118464	0	1
Information and communication	1373	0.0298673	0.170223	0	1
Financial and insurance services	1001	0.0217751	0.1459499	0	1
Real estate activities	441	0.0095932	0.0974751	0	1
Professional, scientific and technical serv.	4171	0.0907331	0.2872323	0	1
Other scientific services	3373	0.0733739	0.2607521	0	1
Education	1508	0.032804	0.1781252	0	1
Health and social work	6484	0.1410485	0.3480754	0	1
Arts, entertainment and recreation	513	0.0111595	0.1050484	0	1
Other services	1874	0.0407657	0.1977491	0	1
Impact of COVID-19 on business activities					

Table 1. *Cont.*

Variable	Obs	Mean	Std. Dev.	Min	Max
Very strongly negative −5	3696	0.0842163	0.2777151	0	1
−4	5074	0.1156151	0.3197664	0	1
−3	6006	0.1368515	0.3436944	0	1
−2	2892	0.0658965	0.2481039	0	1
−1	907	0.0206667	0.1422676	0	1
Balanced/neither nor 0	22,180	0.5053888	0.4999767	0	1
1	175	0.0039875	0.0630215	0	1
2	409	0.0093194	0.0960872	0	1
3	1076	0.0245175	0.1546511	0	1
4	992	0.0226035	0.1486374	0	1
Very strongly positive 5	480	0.0109372	0.1040087	0	1
Establishment size					
1 to 9 employees	13,503	0.293735	0.455477	0	1
10 to 49 employees	14,107	0.306874	0.4612017	0	1
50 to 249 employees	14,665	0.3190124	0.4660989	0	1
250+ employees	3695	0.0803785	0.2718812	0	1

Data source: BeCOVID, own calculations.

4. Theory

The following estimates are based on a dynamic labour demand model (Hamermesh 1993). Here, it is traditionally assumed that firms adjust their employment continuously over several periods, as the associated adjustment costs increase disproportionately. However, the seminal work of Hamermesh (1989) and subsequently Caballero et al. (1997), Abowd and Kramarz (2003), Varejão and Portugal (2007), Nilsen et al. (2007) and Kramarz and Michaud (2010), respectively, have shown that this assumption is not tenable if microdata are used. According to their results, labour demand in competitive markets adjusts disruptively and without further lags, i.e., longer periods in which firm employment is held constant alternate with short periods of rapid labour demand adjustment. Such behaviour indicates either lump-sum or largely linear cost structures (Addison et al. 2014). Under such cost structures, a firm will adjust whenever the additional profits from adjustment, $\Delta\pi(\Delta L)$, are greater than the cost of adjustment, $C(\Delta L)$, with π as profits, L as labour and C as a function of adjustment costs. This results in the following model:

$$L_t = \begin{cases} L^* & if\ \Delta\pi > C \\ L_{t-1} & if\ \Delta\pi < C \end{cases} \tag{1}$$

or

$$L_t = \beta L_{t-1} + (1-\beta)L^* \tag{2}$$

with t indicating the period and * indicating the profit maximizing level of labour demand. Then, β is the share of firms that do not adjust employment to its optimal value. Based on Equation (2), it is also clear that using panel data with short time intervals is much more informative than, for example, a dataset with annual survey intervals. The larger the adjustment costs are, the smaller should be the proportion of establishments that adjust their employment over a single period of time. However, if the survey interval is very large, then almost all establishments will have adjusted their employment without inferring differences in costs. Therefore, data should be available for estimation at least quarterly (Addison et al. 2014). Previous estimates have shown that an adjustment was often completed within one to two quarters (Hamermesh 1993, p. 261). STW can also be interpreted as a way of changing contractually agreed working hours at short notice and without major bureaucratic effort. In this context, it should also be noted that it is often assumed that an adjustment of working hours occurs faster than an adjustment of the number of employees in a recession. In addition to dismissal protection regulations as a cause for such behaviour, labour hoarding due to STW can also preserve specific human capital (Cahuc et al. 2014, p. 137). If rational agents are assumed, then firms also consider all future firing costs when hiring, and vice versa. Therefore, there should then be approximately symmetric behaviour, even if direct hiring and firing costs differ.

Manning (2006), on the other hand, takes a different approach to derive a dynamic model of labour demand when the labour market corresponds to a monopsony (or an oligopsony). Starting from the determinant supply function in the monopsony, employers must raise wages to attract more workers. This implies two things. First, if more workers are to be hired, higher wages must be paid to each additional worker. Second, hiring costs for larger firms are ceteris paribus higher. Thus, hiring costs not only increase disproportionately, but also depend on the previous level of employment. Conversely, firing costs should be much lower for firms on a monopsony, since they can save costs on high wages. Thus, the adjustment costs are probably asymmetric. However, employees also acquire company-specific human capital, which can lead to labour hoarding (Crimmann et al. 2012; Bellmann et al. 2013). Moreover, rationally acting employers should also include future adjustment costs in their decision here, so that it is hardly possible to make statements about differences in the adjustment speed between hiring and firing.

The situation is similar in the case of a shortage of skilled labour with wage competition. If different firms compete for a limited number of applicants, they have to pay higher wages in order to attract new employees or to prevent the workforce from leaving (Cahuc et al. 2006). However, all firms present in a market then compete with each other regardless of their size, so that costs are incurred equally by small and large firms. The size of a firm is then only a sign of higher productivity and the associated ability to attract more employees through higher wages (Cahuc et al. 2006).

Moreover, the adoption of STW has further implications. Experience from Germany and France shows that companies that suffered severely from the economic downturn in the Great Recession of 2008/2009 used STW as a flexible and less-costly solution to protect their core workforce from unemployment, and were able to put these workers back to work immediately when the economy began to recover (Crimmann et al. 2012; Cooper et al. 2017; Cahuc et al. 2018). This should indicate a much faster adjustment process of STW compared with changes of employment through external hiring and dismissals. Nevertheless, there are also studies revealing inefficiencies in the use of STW. Cooper et al. (2017) point to an extended filling time for vacancies. Cahuc and Nevoux (2019) use French data to show that firms may use STW too intensively, leading to significant production losses. This would then indicate a slowdown in adjustment processes.

Hence, we are able to formulate the following hypotheses:

H1: *If STW increase firms' ability to preserve existing jobs in the short-run, the use of STW should speed up the employment adjustment for the personnel actually working in the respective establishments.*

H2: *If STW decrease firms' ability to adjust employment, the use of STW should prolong the adjustment time of firms' total workforce.*

The implications regarding the asymmetry of costs and differences in adjustment behaviour can be tested using the econometric methods applied.

5. Descriptive Analysis and Empirical Model

5.1. Descriptive Analysis

Based on data from the Federal Employment Agency, Figure 1 shows the development of the number of short-time workers over time at the macroeconomic level. Immediately after the beginning of the pandemic, the number of short-time workers strongly increased and reached the peak in April and May 2020, with approximately 6 million people being on STW. After the peak, the number declined quickly, increased again until February 2021 and then declined again. This development of the number of short-time workers is supporting the assumption that STW was used as a quite flexible labour market scheme in Germany during the pandemic.

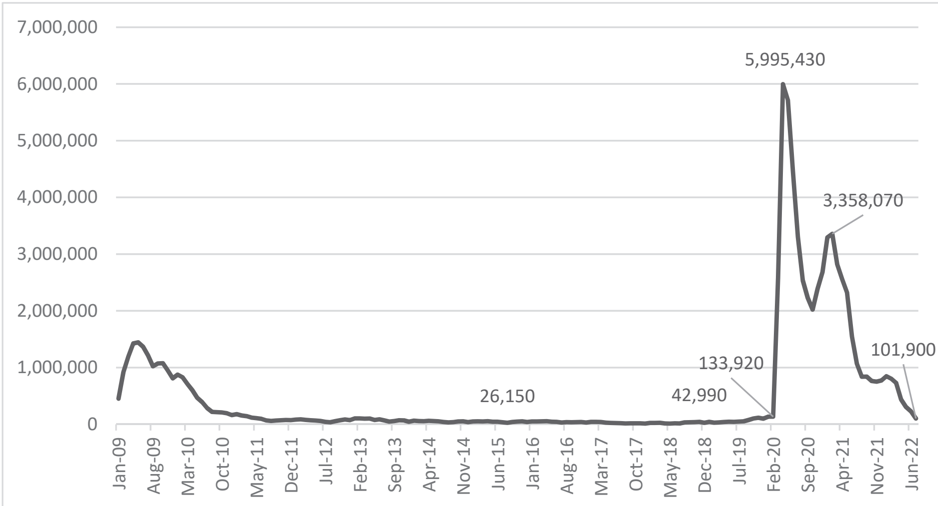

Figure 1. Total number of short-time workers. Data source: Statistic of the Federal Employment Agency, 21 February 2023.

However, as Figure 2 shows, there were large differences in the use of STW across different industries. The industries adopting STW most intensively in April 2020 were manufacturing, trade and food services.

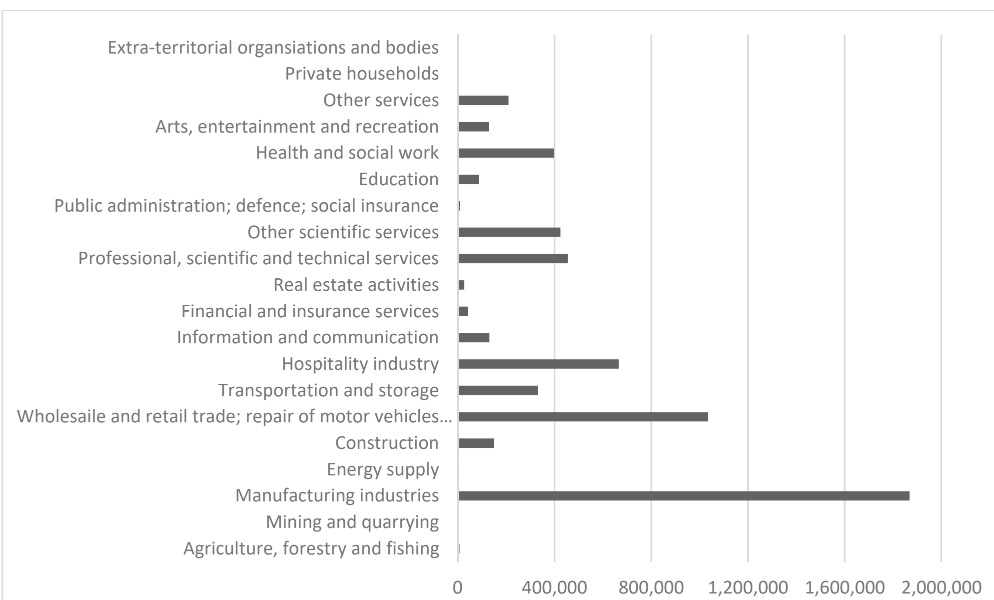

Figure 2. Number of short-time workers by industry, April 2020. Data source: Statistic of the Federal Employment Agency, 20 February 2023.

Moreover, it is evident there are differences not only across industries but also on an establishment level. As the data from the Federal Employment Agency does not provide information at the establishment level, we ran descriptive analyses based on data from the BeCOVID survey. Figure 3 shows the development of the usage of STW during the survey period, starting in August 2020 and ending in August 2022. The *y*-axis shows the mean number of short-time workers by establishment, aggregated by wave, while the solid line shows the amount and the dashed line the development from wave to wave. These descriptive results also support the idea that STW was used quite flexibly, with quick adjustments from month to month during the pandemic.

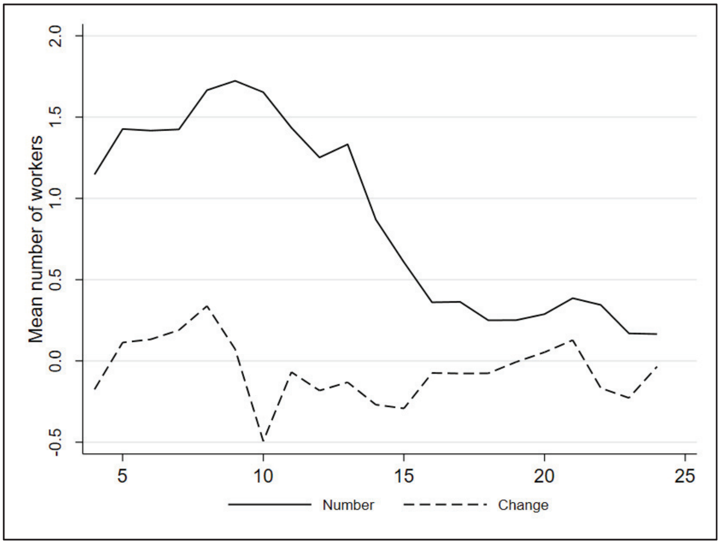

Figure 3. Number of short-time workers and change in the number of short-time workers (mean by wave). Data source: BeCOVID, own calculations with weighted data.

Figure 4 presents the weighted mean number of short-time workers by establishment size. The results provide descriptive evidence that there are huge differences in the adoption of STW between firm size categories. Regarding the number of short-time workers, the largest adoption of STW was by large establishments with more than 50 employees, while small- and medium-size establishments played only a minor role for the total number of workers being on STW. During the first months of the pandemic, large establishments had on average between 10 and 15 workers who were on STW, with only between two and four workers at medium-size establishments (with 10–49 employees) and between zero and one at small establishments (with 1 to 9 employees).

Similarly, we examine the share of short-time workers at establishment level instead of the total amount. Figure 5 exhibits the share of short-time workers to all employees in per-cent, aggregated by wave. The Figure show quite similar curves for all three establishment size categories, while the curve for the large establishments is slightly flatter: at the peak, small- and medium-size establishments had a share of about 15 percent of all employees being on STW, while large establishments had approximately 10 percent. The curves for small- and medium-size enterprises also record a second small peak in February 2022 (wave 21/22), which cannot be found for large establishments. Overall, from a descriptive point of view, we demonstrate that STW played an important role for establishments of all sizes during the pandemic, even though the total amount of STW at the macroeconomic level was driven by large establishments.

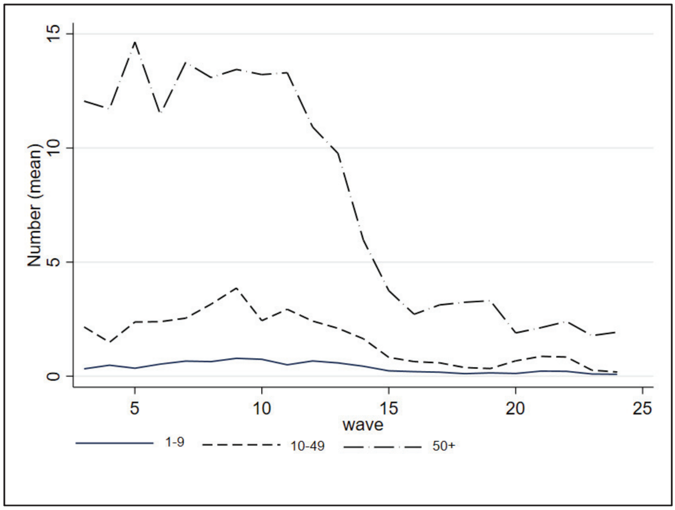

Figure 4. Mean number of short-time workers by establishment size class. Data source: BeCOVID, own calculations with weighted data.

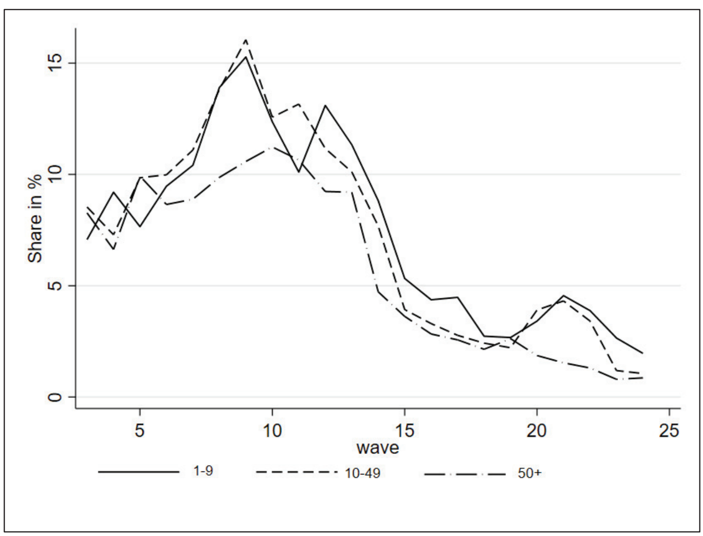

Figure 5. Share of short-time workers to all employees (in percent) by establishment size class. Data source: BeCOVID, own calculations with weighted data.

5.2. Empirical Model

The results below are based on a dynamic labour demand model and are obtained using a two-stage generalized method of moment (GMM) system estimator that uses both lagged differences of the exogenous variables and their levels as instruments (Arellano and Bover 1995; Blundell and Bond 1998). Equation (2) yields the empirical model to be estimated:

$$L_t = \beta L_{t-1} + \gamma X_{it} + \mu_i + \varepsilon_{it}, \quad (3)$$

with X_{it} as the additional covariates determining labour demand, L^*, μ_i as establishment-specific heterogeneities, and ε_{it} as the error term. Such a model cannot be estimated consistently with a panel estimator because the errors, ε_{it}, are autocorrelated due to the lagged endogenous variable L_{t-1}. Arellano and Bond (1991) therefore propose an instrumental variables approach, which is then estimated using GMM. As a first step, we take first differences of both sides of Equation (2) to eliminate establishment-specific heterogeneities:

$$\Delta L_t = \beta \Delta L_{t-1} + \gamma \Delta X_{it} + \Delta \varepsilon_{it}. \tag{4}$$

To eliminate the correlation between ΔL_{t-1} and $\Delta \varepsilon_{it}$, valid instruments are required. All data of L, which are older than 2 periods, are suitable for this purpose. The errors $\Delta \varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1}$ are correlated with $\Delta L_{t-1} = L_{t-1} - L_{t-2}$, but not with L_{t-3}. This is also true for all periods, *t-n*, further back, for both the lagged endogenous variable and the other exogenous covariates. This leads to a set of instrumental variables that are on the one hand larger than the number of parameters to be estimated and on the other hand do not have to be the same in each period. Therefore, GMM is a suitable estimation method.

The empirical model used in our study is an extension of the original Arellano–Bond GMM estimator, which is particularly suitable for datasets with many observed units and few time points of observation. This is called the GMM system estimator (Arellano and Bover 1995; Blundell and Bond 1998). One condition to apply this model is, on the one hand, that autocorrelation with the errors is not present and, on the other hand, that the firm-specific effects are not correlated with the first difference of the dependent variables. Since, based on the modelling, the first difference of the errors will be autocorrelated, the rejection of a test for autocorrelation does not mean that the model is misspecified. However, rejection of the null hypothesis at higher orders means that the moment conditions are not valid. Then, it is also possible to determine parameters for time-invariant exogenous variables in two-step GMM models (Kripfganz and Schwarz 2019). Moreover, we used a Windmeijer bias-corrected (WC) estimator to calculate robust standard errors (Windmeijer 2005). The BeCOVID data is a rotating panel. After a maximum of six participations, an establishment was rotated out of the sample. Therefore, the number of possible instruments is limited and we did not test the sensitivity to a large number of instruments (cf. Roodman 2009).

The endogenous variable is defined as the logarithm of the actual number employed by the firm. This number does not include short-time workers, although they are still formally tied to the firm. Since a dynamic model is estimated here, the endogenous variable lagged by one period is also one of the covariates. In addition, a dummy for whether the establishment uses STW or the log number of short-time workers is used. Since STW is not an economic explanation for determining optimal employment, this information is used only as an interaction variable with the lagged number of employees to describe differences in the speed of adjustment. Other exogenous variables include establishment assessments of economic development (11-digit ordinal categories) and liquidity, the existence of a works council, whether the establishment exports or is foreign-owned, the average wage in June 2020, and time, industry and establishment size dummies. Instruments used are levels as well as first differences. Additional instruments are the levels and first differences of the endogenous variables lagged by more than one period.

Implicitly, we use here a model with two factors of production, labour and capital. Therefore, we need to add the cost of capital of firms to our empirical model. We assume that these are a combination of general market conditions, i.e., the average interest rates businesses have to pay for a loan, and establishment-specific factors such as the liquidity of the firms. While the first factor is time-specific and does not vary across firms, it is deleted to consider time-specific heterogeneities. However, we still control for firm-specific factors of the cost of capital such as liquidity.

6. Results

Table 2 contains the results of the basic model, in which only the influence of the STW on the demand for labour plays a role. The results for the Arellano–Bond autocorrelation test show the expected results, so that the estimates can be considered as valid. The outcome is calculated using robust standard errors proposed by Windmeijer (2005). Column (a) contains the simplest model. The dependent variable is defined as the entire workforce including short-time workers. In addition to the lagged endogenous variable, the estimate also includes the covariates described above. The estimated parameter for the lagged endogenous variable is 0.775. Assuming, as Addison et al. (2014) do, that adjustment costs do not rise disproportionately, the value suggests that about 22.5% of establishments adjust their permanent employment completely within two survey waves, which is approximately one month. This would be significantly faster than estimates for Germany based on annually repeated surveys (e.g., Jung 2014) and in line with results that can be obtained for the duration of the staffing process in Germany from the IAB Job Vacancy Survey (Carbonero and Gartner 2022). In addition to the lagged endogenous variable, several dummy variables are also statistically significant. This is also true for prior pay in 2020, the share of unskilled workers, establishments that also sell their products and services abroad, and establishments that have a works council. All variables appear to be characteristic of larger establishments. Since the results for these covariates do not change for the other estimates, they are not considered further below.

Table 2. Arellano–Bover/Blundell–Bond two-step GMM system estimator of a dynamic labour demand model.

	(a) Employment Incl. STW	**(b) Employment Incl. STW**	**(c) Employment Incl. STW**	**(d) Employment Excl. STW**	**(e) Employment Excl. STW**
Log. of lagged endogenous variable $(t-1)$	0.775 ** (0.062)	0.741 ** (0.069)	0.768 ** (0.056)	0.228 * (0.090)	0.260 ** (0.099)
Interaction variable: Log. of lagged endogenous variable $(t-1) \times$ (use of STW, no. of STW)		0.002 (0.001)		−0.009 * (0.004)	
Interaction variable: Log. of lagged endogenous variable $(t-1) \times$ (use of STW, yes = 1, no = 0)			0.008 (0.008)		−0.250 * (0.113)
Log. of average daily remuneration in 2020	0.053 ** (0.017)	0.065 ** (0.020)	0.055 ** (0.016)	0.187 ** (0.056)	0.181 ** (0.067)
Share of unskilled workers	0.107 ** (0.034)	0.122 ** (0.037)	0.109 ** (0.031)	0.367 ** (0.110)	0.253 * (0.125)
Supply of goods and services … (base: exclusively or predominantly within Germany)					
Predominantly outside Germany	0.015 (0.014)	0.011 (0.015)	0.016 (0.015)	0.065 (0.050)	0.090 (0.059)
In roughly equal parts within and outside Germany	0.029 ** (0.011)	0.029 * (0.012)	0.028 * (0.011)	0.044 (0.046)	0.089 (0.057)
Predominantly in foreign ownership	−0.026 (0.016)	−0.027 (0.018)	−0.026 (0.017)	−0.071 (0.066)	−0.114 (0.076)

Table 2. *Cont.*

	(a) Employment Incl. STW	(b) Employment Incl. STW	(c) Employment Incl. STW	(d) Employment Excl. STW	(e) Employment Excl. STW
Works council	0.054 ** (0.017)	0.060 ** (0.018)	0.054 ** (0.015)	0.134 ** (0.040)	0.135 ** (0.046)
Impact of the Corona pandemic on business activities (10 dummies) #	yes *	yes	yes	yes **	yes **
Liquidity (5 dummies) ##	yes	yes	yes	yes	yes
Dummies indicating industries (18 dummies)	yes	yes	yes	yes **	yes **
Dummies indicating firm size (3 dummies)	Yes **	Yes **	Yes **	yes **	yes **
No. of observations (firms; instruments)	16,169 (6547; 188)	14,882 (6148; 271)	14,951 (6167; 267)	14,832 (6133; 271)	14,832 (6133; 267)
Wald test χ^2 (df.)	256,740.53 ** (64)	226,025.24 ** (63)	227,057.01 ** (63)	14,810.92 ** (63)	11,454.93 ** (63)
First order (z-value)	−3.8511 **	−3.3483 **	−3.553 **	3.3222 **	2.5863 **
Second order (z-value)	1.2632	1.3527	1.3893	−0.0745	−0.4514

Note: BeCOVID panel waves 1 to 24, Windmeijer (2005) WC-robust standard errors. ** and * denote significance at the 0.01, and 0.05-level, respectively. # 10 dummies from very strong negative impact to very strong positive impact, base: no impact, ## 5 dummies from "1 to 2 weeks" to "generally sufficient reserves", base: "1 to 2 weeks". The regressions contain additional dummies indicating the different waves and a constant.

Columns (b) and (c) contain estimates with the same endogenous variable supplemented by a STW variable as an additional covariate. Since larger firms (may) use STW both more frequently and more intensively, the number of short-time workers or a corresponding dummy variable would have no further information. Instead, these variables are interacted with the lagged endogenous variable so that the impact on the speed of adjustment can be measured. Although both parameters are positive, indicating a slower adjustment process, they are rather small and insignificant. Hence, there is only little support for hypothesis 2.[1]

The estimates in columns (d) and (e) are derived from a different endogenous variable. Here, STW is excluded from the number of workers. In column (d), the lagged endogenous variable is interacted with the number of STW, and, in (e), a dummy indicating the use of STW is applied instead. This has serious implications for the estimated parameters for the lagged endogenous variable. The estimated values are now 0.228 and 0.260, respectively, indicating that on average about three-quarters of establishments adjust their employment within one month. Since the estimated interaction variables are both negative and statistically significant, this suggests an even faster adjustment when STW is used by the firms. In the case of column (e), the values cancel out almost entirely, so that, according to this estimate, the use of STW leads to an adjustment of employment within one month only. Due to the facilitated conditions regarding the use of STW in Germany during the pandemic, this result seems quite reasonable.

Table 3 contains the results of estimates of differences in adjustment costs between firms that lay off employees and other entities. It seems that the speed of adjustment is slower in establishments that reduce total employment (column a). However, this is probably not due to the use of STW as the results in column (b) are not significant. When the number of short-time workers is subtracted from the number of employees, the picture is somewhat different. Not surprisingly, the use of STW seems to accelerate the reduction of employment actually needed in the workplace (column d).

Table 3. Arellano–Bover/Blundell–Bond two-step GMM system estimator of a dynamic labour demand model (change in employment).

	(a) Employment Incl. STW	**(b) Employment Incl. STW**	**(c) Employment Excl. STW**	**(d) Employment Excl. STW**
Log. of lagged endogenous variable $(t-1)$	0.816 ** (0.056)	0.804 ** (0.053)	0.260 ** (0.063)	0.337 ** (0.118)
Interaction variable: Log. of lagged endogenous variable $(t-1)$*(use of STW, yes = 1, no = 0)		0.011 (0.010)		−0.192 * (0.082)
Interaction variables: dummy indicating decreasing employment (endogenous variable) *				
Log. of lagged endogenous variable $(t-1)$	0.005 * (0.002)	0.013 (0.007)	−0.038 (0.045)	−0.105 ** (0.010)
Interaction variable: Log. of lagged endogenous variable $(t-1)$*(use of STW, yes = 1, no = 0)		−0.011 (0.012)		0.144 (0.137)
No. of observations (firms; instruments)	16,169 (6547; 257)	14,951 (6167; 388)	14,832 (6133; 237)	14,832 (6133; 381)
Wald test χ^2 (df.)	327,778.57 ** (65)	321,145.50 ** (65)	15,109.70 ** (62)	14,717.79 ** (65)
First order (z-value)	−3.8016 **	−3.4141 **	3.7926 **	−3.7435 **
Second order (z-value)	1.2271	1.3363	−0.0586	−0.0289

Note: BeCOVID panel waves 1 to 24, Windmeijer (2005) WC-robust standard errors. ** and * denote significance at the 0.01, and 0.05-level, respectively. Also included are 10 dummies from very strong negative impact to very strong positive impact, base: no impact, and 5 dummies from "1 to 2 weeks" to "generally sufficient reserves", base: "1 to 2 weeks". The regressions contain additional covariates: log. of average daily remuneration in 2020, share of unskilled workers, area of supply of goods and services, foreign ownership, the existence of a works council, dummies indicating the different waves, business activities, liquidity, industries firm size and a constant. Please see Table 1 for further details.

7. Discussion

There is hardly any literature on the use of STW on a large-scale level. Fitzenberger and Walwei (2023) point out that establishments used short spells of STW during the pandemic, so that they conclude that an overuse of STW was unlikely. This argument is supported by our result that the adjustment process occurs very fast. Comparing our results with those of the existing literature using firm-level data, they are mostly corroborated, but there are also remarkable deviations. First, the rapid rates of adjustment postulated by the literature are apparent when high-frequency data are used. The one to two quarters reported by Hamermesh (1993, p. 261) does not contradict our estimates. In addition, the faster adjustment speed when STW is accounted for can also be taken as an indication that labour hours are adjusted faster than the number of workers. This also confirms the studies that present STW as an efficient way of labour hoarding to resume the production of goods and services quickly after the end of the recession (Crimmann et al. 2012; Cooper et al. 2017; Cahuc et al. 2018). However, there is no or very weak evidence of potential negative effects. In contrast to Cooper et al. (2017), STW appears to cause no or very little delay in employment adjustment. In addition, it appears that it is possible to recall workers from STW back to work quasi-immediately. This also dispels the concerns that STW is used too intensively beyond what is efficient (cf. Cahuc and Nevoux 2019). Differences in national legislation on STW may also play a major role here. Nevertheless, from our work, we can conclude that STW does not lead to significant production losses because of its inefficient use.

8. Conclusions

During the COVID-19 pandemic, many countries adopted STW schemes on a large scale to allow for a flexible and fast adjustment of employment. Thus, unemployment was avoided and employment could rapidly rebound after the COVID-19 'crisis-related' shutdowns. However, both the OECD and IMF questioned the efficiency of the STW schemes in the reallocation of workers from unviable jobs to industries and firms with better prospects. Furthermore, adjustments of regulations of STW during the crisis provided additional incentives to lock-in employees in their current jobs. Estimating dynamic labour demand models to investigate the effect of STW on employment, we are able to analyse the behaviour of establishments during the pandemic. The high-frequency establishment-level data allow the estimation of dynamic labour demand models for 24 waves of the Survey *Establishments in the COVID-19 crisis.* To the best of our knowledge, this study is the first for Germany and is among few others that use high-frequency employer data to estimate dynamic labour demand. The results differ significantly from those obtained, for example, using panel data with an annual interview interval. It becomes clear that the adjustment processes take place much faster than described by previous studies. This shows the special relevance of the data we used for our analyses.

Both the implementation of exceptional STW measures to increase the attractiveness of STW during the pandemic and the incentives created to finish individual STW episodes contributed to the high speed of the adjustment process. To account for the cost efficiency of STW, the OECD (2021, 2022) favoured the co-financing by establishments, e.g., by an "experience rating" scheme, which is designed in such a way that establishments using STW allowances over a long time during difficult times have to make repayments or pay higher social security contributions during normal times. Against the background of our empirical results on the rapid exit of establishments from their use of STW and the short spells of STW reported by Fitzenberger and Walwei (2023), such a strategy seems to be unnecessary.

Moreover, our empirical results corroborate the hypotheses that firms' ability to preserve existing jobs in the short-run decreases the time necessary to adjust the number of employees actually working in the respective establishments. In addition, our results show that the employment adjustment in establishments using STW during the COVID-19 crisis occurred almost immediately, within one month only. Thus, in contrast to the evidence for France, our analyses do not reveal any lock-in effects. Furthermore, the speed of adjustment is slower in establishments with reductions in total employment.

Despite the obvious advantages of a high-frequency panel to estimates adjustments processes, there are some caveats with the data. One is the lack of current wage information, and the other the rather short length of the panel. Both could affect the validity of the outcome and should be overcome when new high-frequency data on firms are collected in establishments' surveys.

Further research should be devoted to merging establishment and administrative data records on STW and full employment biographies (vom Berge et al. 2021). Of interest is also more information about the establishments' biographies available from the Establishment History Panel (Ganzer et al. 2021). Additionally, the mass and fluctuating use of STW schemes suggests considering simplified criteria and procedures (Weber and Yilmaz 2023).

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Note

1 The estimation results without the use of robust standard errors are statistically significant in each case. However, the small values rather indicate a small influence. The *p*-values for robust standard errors are 0.2 in each case. The estimation results are available from the authors on request.

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Youth Entrepreneurship in Germany: Empirical Evidence on the How, the Why, the How Many, the Who and the When

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Abstract: Youth entrepreneurship is an increasingly prominent aspect of entrepreneurship support policies, but there is surprisingly little relevant research-based empirical evidence. This research gap is particularly noticeable when it comes to the personal and contextual factors that steer young people's decision to start a business. Using statistically representative survey data from the Global Entrepreneurship Monitor for Germany, we apply logit regressions to determine the influence of 10 independent variables on the likelihood of starting a business. We distinguish between 18–24-year-olds and 25–64-year-olds as well as between founders and non-founders. Self-efficacy in entrepreneurial skills, fear of failure and gender are the strongest influencing variables for the person-related factors and knowledge of other founders for the contextual factors. For younger people, the formal level of education and the perception of local entrepreneurial opportunities do not play a role in the decision to start a business, whereas they are very important for older people. Our results suggest that start-up promotion policies should explicitly address the empirically proven factors of youth entrepreneurship instead of a 'one size fits all' policy for new businesses, regardless of the age of the founders.

Keywords: youth entrepreneurship; entrepreneurship; Germany; spatial context; demographics; entrepreneurship policies; Global Entrepreneurship Monitor (GEM)

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1. Youth Entrepreneurship: Relevance, Research Gaps and Opportunities for Academic Research

Entrepreneurial activities in the form of new venture creation are widely interpreted as drivers of economic development and growth (Wong et al. 2005). This statement holds true for each geographical dimension at the supranational level (e.g., the EU), the national level (e.g., Germany) and the regional and local level (i.e., the subnational level) in particular (Feldman 2001). New ventures are created by founders (either independently or collaboratively) whose personal attributes may have a statistical, but occasionally also causal, relationship with the start-up propensity of an individual and the probability of the success of this venture (e.g., growth, survival) (Gartner et al. 2004). One of these personal attributes is the age of the individual when they decide to start a business—or apply for a job (Cucculelli and Micucci 2019; Lévesque and Minniti 2006).

The popular notion is that new ventures are mainly started by young people; indeed, this stereotype has some evidence in the primary global start-up region referred to as 'Silicon Valley'. The founders of leading tech firms were indeed quite young when they started their business such as Apple Inc. (two of the three founders, Steve Jobs and Stephen Gary Wozniak, were 21 and 25 years old, respectively, when they started the business in 1976) and Windhorst Electronics GmbH (founded by the German serial entrepreneur Lars Windhorst in 1993 as a 16-year-old schoolboy). However, this is the exception rather than the rule in developed countries. While in many developing countries young people are indeed more entrepreneurial than the older generation—given the age structure in such countries, young people often comprise the largest age group among entrepreneurs in absolute terms—the situation in high-income countries is completely different. Here, the middle-age groups (35–44 and 45–54) are the most entrepreneurial cohorts, both in absolute and relative terms (GERA 2023). The age distribution of the total population in such countries differs significantly from those in developing countries, where people over 50 currently comprise the majority. In absolute terms, of course, this has an impact on the number of young entrepreneurs compared to older entrepreneurs. When it comes to the economic, technological and societal effects of the age of the founders, there are comparative advantages of either age group in terms of creativity, flexibility, (low) transaction cost and (sufficient) time for return on investment for young entrepreneurs as well as advantages in terms of work experience, start-up experience, capital and networks for older entrepreneurs (for Germany see, e.g., Sternberg 2019). In most high-income countries, the middle-age group shows the highest propensity to start a business, making an inverted U-curve a frequent diagram form of the probability to start a business during their lifetime (Guerrero et al. 2021).

Nevertheless, in addition to the more general evidence presented above, there are many open research questions regarding youth entrepreneurship, both from a theoretical and an empirical perspective. While there is some empirical evidence of youth entrepreneurship, it is mainly restricted to emerging/developing countries (see, e.g., Burchell and Coutts 2019; van der Westhuizen and Goyayi 2020; or Baluku et al. 2019), where starting a business often has a different economic and social relevance than in high-income countries.

When dealing with young entrepreneurs, most studies in the latter countries address only university students or graduates, who are not emblematic of all young entrepreneurs, no matter which country type is considered (e.g., Turker and Selcuk 2009; or Georgescu and Herman 2020). In particular, little is empirically known about the specific mechanisms, attitudes, competencies and motivations of young entrepreneurs compared to older entrepreneurs (Geldhof et al. 2014; see also the critique described in Maleki et al. 2021). The same is true in the case of theoretical explanations. Several of the established theoretical attempts to explain an individual's decision to start a venture (or to be employed) do *not* work for very young founders—or have at least not yet explicitly and systematically been tested for young founders (e.g., trait approaches such as the personality attributes; demographic attributes such as gender, migration background, precise age or start-up experiences; start-up motivations; skills and the like). Accordingly, we do not know whether (and how) these aspects have changed over time, e.g., whether they have changed during the COVID-19 pandemic in a way that, besides entrepreneurship, makes/made young people suffer in a particular way and at a certain level of intensity compared to older people (Boris et al. 2021; Gavriluță et al. 2022). This relative lack of theoretical and, moreover, empirical research on youth entrepreneurship is surprising given the strong correlation (also among policymakers and their effort to support young ventures and/or young entrepreneurs) between young ventures and their seemingly young founders.

In a nutshell, a combined view of theoretical and empirical academic work on youth entrepreneurship shows a relatively large number of publications on entrepreneurial intentions (e.g., Kaya et al. 2019; Shirokova et al. 2022) and fear of failure as an obstacle to starting a business, with young people being less risk averse, (Tubadji et al. 2021). Moreover, youth self-employment is a prominent aspect of research on youth entrepreneurship, often based on data from the UN or the International Labour Organization. However, demographic factors such as gender or education as well as institutional or contextual factors of the respective country or subnational region are under-researched topics in studies on youth entrepreneurship.

For some of the described empirical research gaps, the simple reason for youth entrepreneurship being an under-researched topic within the academic domain of entrepreneurship is the lack of primary internationally comparable and panel-like data. When it comes to survey data, the Adult Population Survey (APS) of the Global Entrepreneurship Monitor (GEM) has, by far, the largest and oldest international comparable database, providing the exact age (in years) at the time of the interview (for details on the APS questionnaires, see Reynolds et al. 2005; Bosma 2012; Bosma et al. 2012; and www.gemconsortium.org, accessed on 22 July 2019).

This paper's focus is on youth entrepreneurship in Germany. This country provides a particularly compelling case for studying these questions. Even compared to other high-income countries, Germany has a low overall entrepreneurship rate (GERA 2023; Sternberg et al. 2022) but a large number of well-educated young people and a strong overall economy (World Bank 2021). Moreover, the country suffers from a lack of qualified younger people (compared to the available jobs for such people), which is closely related to the overall age structure of the population (many older and fewer young people) and, consequently, of the employees in total. While the total population slightly increased in recent years due to immigration, this has not yet helped to solve the severe labour market problems. Hundreds of thousands of jobs cannot be filled because of a shortage of skilled workers in both well-paid jobs (industries such as software or mechanical engineering) and low-paid jobs (in industries such as health services and the care sector (Brenke 2022). One result is the power of the few: the relatively few very well-educated people in shortage occupations have a very good bargaining position and can negotiate extremely favourable working conditions. Given a traditionally not-very-entrepreneurial-prone society and the high opportunity cost of starting a business by highly qualified labour in Germany, the low overall start-up rate in Germany is a logical consequence.

However, the situation could potentially be different for young people. Young people's aspirations for their lives, careers, and finances change over generations and usually differ from those of their parents or grandparents. For example, younger people, at least in Germany, attach more importance (than older people) to the meaning of work, a lower daily and lifetime working time (which is also supposed to be very flexible) as well as the compatibility of work and family, while career and a high and regularly rising wage have become relatively less important (Deutsche Shell Holding GmbH 2019). This may also affect the decision in favour of starting a business or working as an employee. Indeed, a recent analysis published as part of the annual Global Entrepreneurship Monitor (GEM) Country Report Germany shows that younger people who are starting a business exhibit somewhat different entrepreneurial motivations than older entrepreneurs (see Sternberg et al. (2022) for the most recent GEM Country Report Germany), particularly regarding the fact that the new business 'should make a difference'.

Based on individual data from the Adult Population Survey (APS) of the GEM Country Report Germany for a sufficiently long period, we address four research questions. First, we measure in a descriptive part of our paper how frequent youth entrepreneurship is and has been during the last two decades in Germany (compared over time and across countries). Second, we analyse how the young founders themselves differ in terms of personal attributes from older founders. Third, we investigate how young founders differ from non-entrepreneurial young Germans in terms of entrepreneurial perceptions and attitudes (mirroring the context in which they live) as well as personal attributes. Finally, we provide some empirical evidence of the factors in young people's decision to start a business (instead of working for an employer) compared to the rest of the population. These factors are divided into personal attributes and contextual aspects.

In this paper, we provide the first empirical analysis and assessment of the prevalence of youth entrepreneurship in Germany and the relevant individual factors. Our study contributes to two highly relevant areas of research. First, this paper is an investigation into the amount of youth entrepreneurship in Germany that shares many entrepreneurship attributes with other high-income countries such as low start-up rate compared with low-income countries, high impact of knowledge-intensive products for the country's global competitiveness, emerging attention of policymakers to entrepreneurship in general and of young people as the founders of such ventures in particular. At a time when poorer countries confront unprecedented increases in population and developed countries have ageing populations, we provide important insights into the relationship between demographic structure, aggregate entrepreneurship and growth (Lévesque and Minniti 2011). Second, our analysis addresses the important question (both from an academic and a government policy perspective) of which person-related and contextual factors have an impact on a young individual deciding to start their own venture instead of searching for a job as an employee. While there is a vast amount of literature on start-up decisions in general, the empirical evidence of youth entrepreneurship is quite scarce—particularly regarding the situation in Germany.

The remainder of the paper is organized as follows. In the next section, we describe the literature on youth entrepreneurship in general and in Germany, as well as the personal attributes and contextual aspects, and our conceptual model and related hypotheses are set out. Section 3 is dedicated to the presentation of our data, the variables and the methods used. The results of our empirical analysis are presented in Section 4. Section 5 discusses our findings, and Section 6 will focus on conclusions and limitations.

2. Literature Review: Theoretical Explanations for and Empirical Evidence of the Volume and the Micro-Level Factors of Youth Entrepreneurship

2.1. Youth Entrepreneurship—Definition, Evidence and Relevance

In the lengthy history of entrepreneurship research, most scholars have not focused their research efforts on the area of youth entrepreneurship. Geldhof et al. (2014) attempted to demonstrate how young this particular research area is by pointing out that there was not only a general lack of studies on youth entrepreneurship in 2014, but most reviews of entrepreneurship literature even failed to mention the significance of the topic. Perhaps stemming from the late maturation of this research area, there is also a lack of a common definition or understanding of the term 'youth entrepreneurship' (Holdsworth and Mendonça 2020). In simpler terms, while people might generally use the term 'youth' to describe the period of an individual's life when they are young, it is a highly subjective term that could vary across countries, cultures or even people's perceptions (UN 2023). To demonstrate this, this study found evidence in the existing literature that some studies might use the term 'youth' to refer to people between the ages of 15 and 20 (Hekman 2007), while others view youth in a much wider context such as between the ages of 15 and 35 (Schøtt et al. 2015; Maleki et al. 2021). However, most researchers define youth as the period of one's life when they are between the ages of 15 and 24 (Hulsink and Koek 2014; Burchell and Coutts 2019), sharing the UN's statistical approach to the topic (UN 2023). In our empirical paper, we define youth entrepreneurship as a phenomenon in which individuals embark on their entrepreneurial journey by initiating entrepreneurial activities between the ages of 18 and 24. This definition is mainly driven by the availability of data as described in Section 3.

In recent years, a positive tendency can be seen in the research activities in this area, partly because young people are increasingly starting businesses partly due to unemployment; thus, the relevance of this topic increases as well (Green 2013; Schøtt et al. 2015; Burchell and Coutts 2019; Maleki et al. 2021). The most recent OECD Employment Outlook (2022) shows that the average youth unemployment rate in 2022 was 15% and 13% in the EU and US, respectively (OECD 2022). There is also increasing evidence from developing countries on youth unemployment (see e.g., Baluku et al. 2019; Blattman et al. 2022; Geza et al. 2022); thus, the problem seems to be posing a significant global challenge. Upon analysing the same problem, Schøtt et al. (2015) found that the economic and social costs of youth unemployment are considerable, especially if people cannot find jobs for long periods. First, one potential consequence of their long-term unemployment might be that their skills will be eroded and their potential to enter the job market continuously decreases.

Second, the high levels of youth unemployment can lead to underutilized human capital and talent (Schøtt et al. 2015).

As a potential solution to this global challenge, studies have found that entrepreneurship might just provide youth with the appropriate avenue to enter the job market (Hofer and Delaney 2010; Schøtt et al. 2015; Boris et al. 2021; Gavriluță et al. 2022). Others have shown that youth entrepreneurship does not only provide the youth with an appropriate avenue for long-term value creation in the economy, but youth entrepreneurship can have a positive impact on the economy by creating jobs and driving innovation, thereby contributing to the overall competitiveness of local economies (Murithi 2013). Moreover, youth entrepreneurs will be in a position where they will inevitably need to develop their skills and knowledge to keep their business afloat, contributing to their personal growth as well (Schøtt et al. 2015; Maleki et al. 2021).

2.2. Factors in Youth Entrepreneurship

Given the described potential economic and political relevance of youth entrepreneurship, the factors that steer it become relevant. This paper will group the factors into two main parts: (1) person-related (or internal) attributes; and (2) contextual (or external) factors. The vast majority of literature on youth entrepreneurship focuses on internal factors such as entrepreneurial intentions (see Turker and Selcuk 2009; Kaya et al. 2019; Mawson and Kasem 2019; Swaramarinda et al. 2022) or demographic factors influencing an individual's entrepreneurial journey in their youth (see Hofer and Delaney 2010; Baluku et al. 2019; Boris et al. 2021; Djordjevic et al. 2021; Marchesani et al. 2022; Santos-Jaén et al. 2022). In this section, a selective discussion will be presented on the factors of entrepreneurship along with their associated variables and their relation to youth entrepreneurship.

Person-related factors influence one's intentions for business venturing studies and the eventual decision to start a business or not. Well analysed, these factors include human capital (including entrepreneurial skills), gender, household income, education and fear of failure as a reason not to start a business (Carland et al. 1988).

Empirical research shows that human capital has a significant influence on one's entrepreneurial intentions and decision to start a business venture. Most studies in this area unanimously agree that education can boost youth attitudes and interests in business venturing (Turker and Selcuk 2009; Geldhof et al. 2014; Maleki et al. 2021), while it also provides opportunities for gaining deeper knowledge of risk assessment, innovativeness and 'know-how' (Hsu et al. 2019). Regarding age differences, Schøtt et al. (2015) found that young entrepreneurs have more extensive education and training than older entrepreneurs. Based on GEM data, research shows that three-quarters of youth entrepreneurs have at least completed secondary education compared to two-thirds of older entrepreneurs, providing them with a higher chance of acquiring entrepreneurial skills.

GEM Global reports as well as GEM-based country reports of over two decades show that men in almost every country are involved in entrepreneurial activities more often than women (Martinović and Lakoš 2012; Schøtt et al. 2015; Pilkova et al. 2019). This is also true for Germany, which is the focus of the empirical core of our paper. Interestingly, gender is also considered an important factor in youth entrepreneurship, as most research papers acknowledge that there is a gender gap in the entrepreneurial activity of the youth (Schøtt et al. 2015; Vamvaka et al. 2020). Some studies suggest that an entrepreneurial career poses higher personal and social risks for young female entrepreneurs than for their male counterparts (Vamvaka et al. 2020). One potential reason for this is that female entrepreneurs might face negative implications in terms of social benefits related to family and children as they tend to have higher levels of domestic responsibility (Schøtt et al. 2015). Schøtt et al. (2015) have analysed other potential reasons for this phenomenon such as a general lack of female role models in the business sector, lower levels of education of young women in many developing countries, less business-oriented networks of women and lack of public support for female entrepreneurs (and young ones in particular) due to less confidence in the success of female-led businesses. When comparing different age groups by gender, academic research fails to provide a country-specific analysis.

The literature on young entrepreneurs often deals with the perception of their own entrepreneurial skills as a factor in entrepreneurial intentions. There is strong empirical evidence that the youth more frequently have the intention to start a venture than adults or senior entrepreneurs, even though they have limited financial resources, life and work experience, and they face greater barriers of entry (Schøtt et al. 2015). It is important to distinguish between the objective availability of such skills and the individual perception of whether or not an individual possesses such skills. While the actual skills will influence the success of the start-up in the mid and long run, the perception of such skills strongly impacts the probability of start-up intentions becoming start-up activity, i.e., whether the business will be created or not. Several studies highlight that senior or adult entrepreneurs tend to have higher entrepreneurial self-confidence as well as a wider array of skills and experiences; thus, they might be more perceptive to entrepreneurial opportunities than the youth (Rehak et al. 2017; Pilkova et al. 2019).

Regarding household income, research shows that youth unemployment is one reason why young people are starting businesses (Green 2013; Schøtt et al. 2015; Burchell and Coutts 2019; Maleki et al. 2021). Unemployment directly correlates with low household income, and the economic and social costs of this phenomenon are considerable. In a comparison between senior and youth entrepreneurs in European countries, Pilkova et al. (2019) showed that the youth in developed countries tend to be discouraged from starting a business, as they rely on good employment opportunities; thus, good opportunities to collect a decent household income in turn decreases their self-confidence by providing them with a safe job opportunity. The same research shows that necessity-driven youth entrepreneurship (as opposed to opportunity-driven entrepreneurship) dominates, as the youth views entrepreneurship as a better career choice than being an employee (Pilkova et al. 2019).

Fear of failure can be defined as a general attitude of fear that encourages one to avoid risk and uncertainty or to take risks and dive into the unknown (Shapero and Sokol 1982; Wennberg et al. 2013; Adam et al. 2018). Interestingly, this factor of entrepreneurship can be considered both internal and external, as it is highly dependent on individual attitudes and behaviour (Tubadji et al. 2021), which have been proven to pass down through generations. Research has also found evidence that an individual's attitude towards risk is influenced by role models and the local cultural context (Wennberg et al. 2013). While there is a general risk-taking or risk aversion that stems from culture, a fear of failure can also be influenced by personality traits, societal norms and regulations. Certain demographics might have a different propensity towards risk-taking (Mather et al. 2012). Based on four experiments, younger adults have shown a weaker preference towards sure gains and a weaker risk aversion for sure losses than older adults, who took outcomes into consideration more heavily when a choice was offered between a certain option and a riskier option. Similar findings have been presented by Schøtt et al. (2015), who found that younger youth (18–24 years) have a slightly higher willingness to take on risk than older youth (25–34 years) and adults (35–64). One explanation is that young people in general have not gained lived experience in self-efficacy, opportunity alertness and risk aversion; instead, they have gained their competencies through their network, social bonds or education (Hoffmann et al. 2005).

Other person-related factors are not that well studied. For example, previous entrepreneurship experiences and/or supporting other new firms as a so-called 'business angel' may have an important impact on an individual's propensity to start another new business and/or to start their own business for the first time.

For the other main group of factors of youth entrepreneurship—the external or contextual ones—the literature mentions external incentives (Tubadji et al. 2021) as well as societal and cultural aspects (Geldhof et al. 2014; Maleki et al. 2021; Tubadji et al. 2021). Many empirical studies configure the context in a geographical sense, for example, by distinguishing between local, regional, national or supranational context (see Sternberg (2022) for a recent overview). The regional context is very often considered to be the most appropriate spatial scale to analyse the contextual factors of both entrepreneurial activities (the decision to start—or not start—a business) and entrepreneurial success (i.e., the survival rate or growth of new ventures). In a nutshell, 'Entrepreneurship is primarily a regional event' (Feldman 2001). Moreover, the temporal context might matter when explaining entrepreneurial activity. For example, Fritsch and Wyrwich (2019) have developed a complex socialist heritage hypothesis to explain the entrepreneurial differences between the Eastern (and former socialist) part of Germany and the Western part. All these contextual factors tend to influence someone's entrepreneurial actions. Contextual differences, especially in quantitative–empirical work and in a spatial interpretation of the context, are often described with the—somewhat imprecise—term 'entrepreneurial culture' (Hayton and Cacciotti 2013). Often, this term is merely a placeholder for non-personal attributes of a territory whose influence on individual entrepreneurship decisions is to be investigated. There is empirical proof that societal and cultural factors could all potentially influence one's intentions to start one's own business as well as influence entrepreneurship's desirability and feasibility (Maleki et al. 2021). Nowiński et al. (2020) found that the positive perception of public support indirectly influences one's entrepreneurial intentions because if someone's demonstrated attitude towards entrepreneurship is supported by the actions, beliefs or attitudes of society, they are likely to continue their actions. Public perception might also play a significant role in influencing the youth's self-efficacy (perception of feasibility) and risk attitudes (Nowiński et al. 2020). Other evidence also demonstrates that even if someone is motivated to start their business by financial gains or other means of achievements—whether it is desire for social success, career success or individual fulfilment—a national culture that encourages and supports entrepreneurial activities is needed (Lee and Peterson 2000). A culture that rewards and motivates venture creation can positively influence the youth's entrepreneurial intentions, especially if there is a cultural aspiration for excellence and competitiveness (Lee et al. 2005). Other studies also support the fact that successful entrepreneurs are created in entrepreneurship-oriented cultures and societies (Watson et al. 1998; Lee and Peterson 2000; Morrison 2000; Adam et al. 2018).

For these contextual factors, which are only briefly described here, there are several methodological options in empirical studies, which are exemplified by the spatial context. First, the data can refer to characteristics of the region in question and represent mean values for all inhabitants of this region, e.g., the GDP/per capita of Region 1 as an economic indicator of the region—undoubtedly an important variable that influences an individual's decision to start a business (Bosma 2012; Bergmann et al. 2016). The data for this variable then come from relevant official data sources such as the INKAR database in Germany. A second option is survey-based individual data from a sample of, e.g., the population (e.g., on the migration background or the gender of the respondents) or start-up experts (who, e.g., assess the entrepreneurial framework conditions of the territory) of the spatial unit in question, which are used in relevant regression analyses after aggregation and calculation of a mean value for the territory in question. For example, the GEM project, the largest and oldest international research consortium for the analysis of entrepreneurship activities worldwide, works in this way. A third option is used much less frequently, especially due to a lack of data, although it offers great potential, as it uses the perception of entrepreneurs or potential entrepreneurs (i.e., the population) to indirectly obtain an assessment of the spatial context—precisely from those individuals whose entrepreneurial activities and decisions are to be explained. This is the methodological approach of this paper (more on this in Section 3).

Contextual factors in the entrepreneurial activities of young people also include their perceptions (instead of real attributes such as the GDP per capita in the surrounding territory) of the geographical context in particular. Of course, individual perceptions of these factors may differ from their actual characteristics. However, it is the perception that is decisive for the actions of the individuals (in this case the young people), not the real environmental conditions. Therefore, there are also indications in the literature of how the perception of, for example, the reputation of entrepreneurs in the society in question, influences entrepreneurial propensity (Tubadji et al. 2021). The same applies to the frequency of media coverage of new businesses and young entrepreneurs (Tubadji et al. 2021) as well as the image of starting a new business as a career option. The perception of entrepreneurial opportunities as good (at present and in the region where the individual lives) also influences the individual's propensity to start a business. If an individual perceives these opportunities as poor, they are unlikely to start a new business anyway. This perception, which of course significantly determines the individual's actual actions, is, therefore, an important context variable (Schøtt et al. 2015). Previous analyses on this topic, however, did not distinguish between younger and older people. In addition, the size of the individual's network is a potentially significant factor in both the start-up decision and start-up success (Schøtt et al. 2015). In particular, networks have a compensatory function, as network partners can, at least partially, compensate for the lack of competence, experience and reputation of younger founders or the lack of customers for the new business (Schøtt et al. 2015). In addition, the network can include other former or current founders who can function as role models (Köllinger et al. 2005; Fritsch and Wyrwich 2019) and increase the propensity to found a business. The empirical results to date regarding such network and role model effects on the decision to start a business do not control for the age of the potential or actual founders.

Although this section has shown that there is clear evidence of the youth having high intentions to start their own businesses, studies have stressed the fact that most results have come from cross-cultural and transnational research. It is recommended that country-level studies be conducted to explore the exact differences on societal, cultural and demographic factors influencing the youth's entrepreneurial intentions (Sieger et al. 2019; Maleki et al. 2021). Our paper addresses this research gap by examining the status of youth entrepreneurship in Germany in an attempt to understand the current status of youth entrepreneurship, the factors in youth entrepreneurship and the cultural and societal factors that influence young people in Germany.

2.3. Youth Entrepreneurship in Germany—Conceptual Model and Hypotheses

In this subsection, we use the described current state of youth entrepreneurship in general—in Germany in particular—to illustrate our hypotheses and construct a conceptual model.

2.3.1. Internal Factors

This paper considers the following six separate person-related factors for its conceptual model:

- Gender;
- Household income;
- Education;
- Business angel activity;
- Perception of own entrepreneurial skills;
- Fear of failure (as a reason NOT to start a business).

The entrepreneurial intention in Germany generally seems favourable; Hekman (2007) has shown that German youth have a positive attitude towards entrepreneurs, as 99% of their survey participants considered entrepreneurs either 'favourable' or 'somewhat favourable'. Most participants either had entrepreneurs in their network or their parents or teachers might have transferred their positive attitudes towards entrepreneurs.

Connecting this with Hoffmann et al.'s (2005) study, we assume that German youth gain their entrepreneurial competencies from their network through social bonds or education. Education and social embeddedness also positively affect one's perception of one's entrepreneurial skills and influences one's propensity to start a business. As the annual GEM Country Report Germany have shown for several years—albeit usually without differentiation by age category—around 40–50% of adults in Germany believe that they have the skills required to start a business. This applies to a lesser extent to younger people (Sternberg et al. 2022). International comparisons of this perception of one's own entrepreneurial skills among 18–24-year-olds show that Germany is approximately in the middle of the field among high-income countries with this value (Schøtt et al. 2015). However, the sources mentioned do not examine the impact of this self-efficacy on the actual decision to start a business. When taking the human capital aspect into greater consideration, Hekman (2007) found that young Germans believe that they have inadequate knowledge of economics and entrepreneurship. Specifically, in his research, he saw only 8% of his participants consider their economic knowledge 'good', while more than 90% of the participants believed that they have 'some' or 'hardly any' economic and entrepreneurial knowledge (Hekman 2007). Studies have also demonstrated that education can significantly boost young people's attitudes and interests in business venturing (Turker and Selcuk 2009; Geldhof et al. 2014; Maleki et al. 2021), as well as provide a deeper knowledge of risk assessment, innovativeness and 'know-how' (Hsu et al. 2019). Thus, Germany might be in a similar position than other high-income countries examined in the cited studies, so we assume that the youth's perceived knowledge of their entrepreneurial skills is a more significant factor in the start-up decision than it is for older people.

Hypothesis 1. *The perception of one's own entrepreneurial skills is an important factor in young people's decision to start—or not start—their own business, and it is relatively more important for younger people than older people.*

Regarding gender differences, it has been found that young German men have stronger entrepreneurial intentions than their female counterparts. While 19% of young men considered entrepreneurship an attractive avenue or career, only 12% of women felt the same. Moreover, only 53% of young women believed that they have entrepreneurial abilities compared to 62% of men. Interestingly, a person's level of education had a significant impact on these answers as well, as most of those who considered themselves to have the necessary skills for entrepreneurship have completed their Abitur. This aligns with prior theory, as several studies have shown that women are more likely to suffer negative consequences from pursuing entrepreneurial intentions than men (Vamvaka et al. 2020). We argue that the lower start-up rates among women in general, and in Germany, are neither innate nor instilled in childhood or early adolescence but are only justified in later phases of life and career, as men and women *then* encounter different framework conditions for the implementation of their entrepreneurial intentions.

Hypothesis 2. *Young women do not differ from young men in terms of entrepreneurial propensity and the obligatory person- and environment-related factors, but these gender differences become relevant for people over 25 years of age.*

The fear of failure as a reason for not realizing an existing start-up intention is dependent on experience, and it is a frequently studied term in entrepreneurship literature (see Section 2). If a person has already had the experience of being discriminated against socially and/or among friends or family in the event of failure in their own new business (or has lost creditworthiness with banks), they are less likely to consider starting another business in the future. In addition, in Germany—in contrast to the US, for example—a second chance is rarely granted after an initial failure. As this is widely known in German society and does not only apply to start-ups, non-founders also know this. Ergo, fear of failure is likely to have a negative effect on the start-up decision for all (young and old) people in Germany. This effect, according to our hypothesis, is smaller for younger people than for older people, as they have had fewer experiences with failure than older people.

Hypothesis 3. *Fear of failure prevents young people from starting a business, though less frequently than older people.*

2.3.2. External or Contextual Factors

Regarding the contextual factors in Germany, this paper considers the following four for its conceptual model:

- Knowing other entrepreneurs who recently started a new business;
- Start-up opportunities in the region in which the respondent is living (own perception);
- Starting a new business as a desirable career choice (own perception of other people's opinions);
- Level of status and respect for those successfully starting a new business (own perception of other people's opinions).

As demonstrated in Section 2.1, the literature also discusses standard external factors of entrepreneurship such as investment opportunities, profit, reputation and media coverage of new businesses (Tubadji et al. 2021), as well as societal and cultural factors (Geldhof et al. 2014; Maleki et al. 2021; Tubadji et al. 2021). Upon analysing the societal factors, Pilkova et al. (2019) found that in developed countries such as Germany, the youth might be discouraged from entrepreneurial actions, as they have a wide range of appropriate job opportunities, which could make entrepreneurship a less attractive career option for them. Lastly, taking societal and cultural factors into consideration, research has proven that a nation's supportive culture and general public support can positively influence one's entrepreneurial intentions. It has also been found that cultural aspirations for excellence and competitiveness have positive influenced youth entrepreneurship (Lee et al. 2005). Younger people, all other things being equal, have naturally had less personal experience and met fewer people in person than older people. This also applies to experience with start-ups and knowledge of other entrepreneurs. Therefore, other factors that are not dependent on the amount of personal experience are relatively more important for younger people than for older people when deciding for or against starting a business. This is especially true for personal factors, while contextual factors are relatively more important for older people, as life and work experience facilitate a realistic assessment of these contextual factors.

Hypothesis 4. *For young people, their own perception of the entrepreneurial environment factors has a weaker influence on their start-up decision than personal factors than for older people.*

Hypothesis 5. *For young people, knowing other entrepreneurs is a less significant factor in the start-up decision than for older people.*

Figure 1 shows our conceptual model with five hypotheses and the factors in youth entrepreneurship in Germany.

The aim of this paper is to test the five hypotheses mentioned above on the basis of a suitable dataset and by means of adequate statistical methods, and thus to contribute to the state of empirical research on youth entrepreneurship.

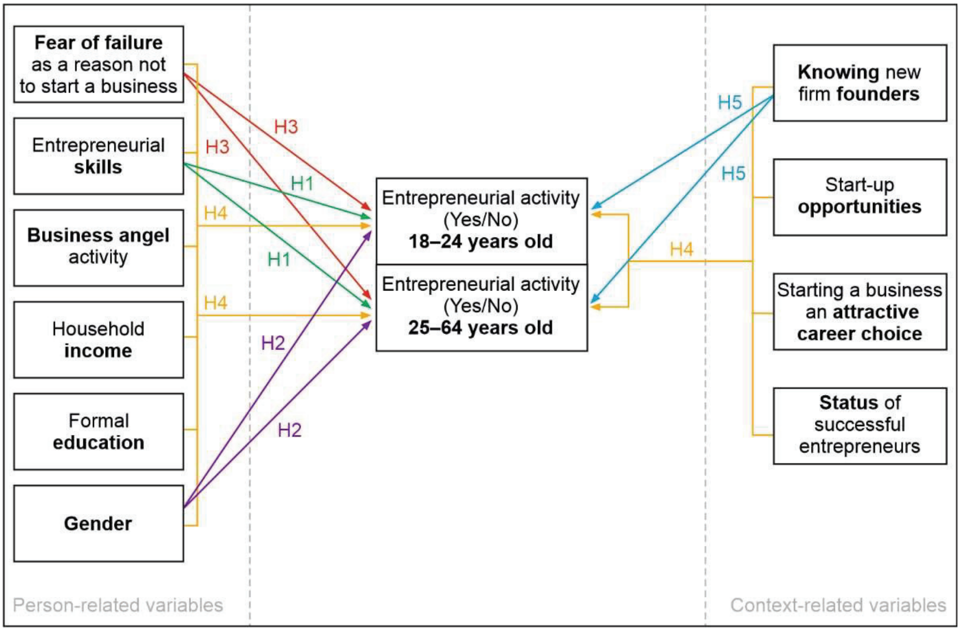

Figure 1. Conceptual model.

3. Data and Methods

3.1. Data

The empirical core of this paper is based exclusively on one data source, which, given the research questions of the paper, is without alternative from both a quantitative and qualitative perspective. We use the German data from the APS of the GEM. One of the many strengths of this entrepreneurship research consortium (the largest worldwide) is the fact that statistically representative data for entrepreneurs (i.e., founders of new businesses) and non-entrepreneurs are available for each country participating in the GEM in the respective survey year including the exact age of the person at the time of the survey. Empirical analyses of Germany, the subject of this paper, can also benefit from the fact that the German GEM team has been involved in this consortium since its inception and that, except for 2007, data are available for each year between 1999 and 2022 (see also the complete list of all annual GEM Country Reports Germany from 1999 to 2022: https://www.iwkg.uni-hannover.de/en/research/research-projects/details/projects/global-entrepreneurship-monitor-gem-country-report-germany, accessed on 22 March 2023; the most recent report also describes the core variables (Sternberg et al. 2022)). In principle, a very long data series with hundreds of thousands of cases is available for Germany from the GEM. In addition to the country reports, the global consortium publishes an annual global report (for the most recent one see GERA 2023). For details on GEM data and methods, see Reynolds et al. (2005) as well as the publicly available GEM Wiki (http://gem-consortium.ns-client.xyz/about/wiki, accessed on 12 June 2012). The entrepreneurship literature contains hundreds of empirical studies based exclusively or partially on GEM data, many of which focus on one country or compare several countries. The completely standardized data for a survey year for the countries involved in each case allow such comparisons to be made completely, or at least to a large extent in the case of intertemporal comparisons for the same or several countries.

Our paper uses data from 2009 to 2018 and pools the data from the individual 10 years to generate sufficiently large samples for the very rare event ‘youth entrepreneurship’. (Please note that, in Germany, entrepreneurship in general is a rare event.) The APS is a household survey (not a survey of entrepreneurs) in which—on average—only some 5% of respondents in Germany are founders of a new business according to the GEM definition. Thus, pooling many years (and controlling for them in the regression models) is crucial. Nevertheless, there is no other data source in Germany that offers more data on youth entrepreneurship over a longer period than the GEM data mentioned.

The target population of GEM is 18–64-year-olds. For our paper, we define 'youth' as 18–24-year-olds, although we could, in principle, also conduct analyses for individual age cohorts. We restrict our analysis to the 2009–2018 survey years. For some variables, analyses for the 2001–2022 period (with more than 105,000 cases for Germany) would also be possible; however, we will only use this for a descriptive overview of the development of the entrepreneurial activity rate over time. Due to changes in the scaling of variables and/or the wording of some variables used since 2019 or before 2009, we will only use data from the 2009–2018 period with 46,937 cases for all other analyses.

The data we use describe (e.g., demographic) characteristics of the individuals surveyed, the new businesses they may have founded and the respondents' perception of the context. Following our conceptual model, the nine independent variables are assigned to two groups: six internal factors describing certain personal attributes of the interviewee and four external factors describing the context in which the interviewee is living and working (in part, however, seen and perceived by the interviewee). All variables are dichotomous, except for household income (which we are using as a dummy variable in our regressions, too). See Table 1 for the definitions, descriptions, values and some measures of each of these independent variables.

Table 1. Definitions, descriptions and values of the variables.

Variable Name	Variable Definition	Values
Dependent		
TEA	Total Early stage Entrepreneurship: respondent involved in a nascent firm or young firm or both	1: yes, 0: no
Independent: person-related		
Businessangel	Respondent has, in the past three years, personally provided funds for a new business started by someone else, excluding any purchases of stocks or mutual funds	1: yes, 0: no
Education	Respondent's highest educational attainment	1: secondary degree and more 0: below secondary degree
Fearoffailure	Fear of failure would prevent the respondent to start a business	1: yes, 0: no
Gender	Respondent gender	1: female, 0: male
HHIncome	Household income (recoded into thirds)	68,100: highest 33% tile 3467: middle 33% tile 33: lowest 33% tile
Skills	Respondent thinks to have the required knowledge/skills to start a business	1: yes, 0: no
youngornotyoung	Respondent's age category	1: 25–64, 0: 18–24

Table 1. *Cont.*

Variable Name	Variable Definition	Values
Independent: context-related		
Goodopp	Respondent sees good opportunities for starting a business in the next 6 months in the area where he/she lives	1: yes, 0: no
Career	In Germany, starting a business is considered a good career choice	1: yes, 0: no
Respect	In Germany, people growing a successful new business receive high status	1: yes, 0: no
Knowent	Respondent knows a person who started a business in the past 2 years	1: yes, 0: no

3.2. Methods

When interviewing the general adult population, involvement in early-stage entrepreneurial activities can be characterized in a binary manner. A person is either actively pursuing a venture creation, be it alone or as part of a group, or is not involved in any such process. The Global Entrepreneurship Monitor captures this information as 'Total early-stage Entrepreneurial Activity' (TEA) with 1 = Yes and 0 = No. Thereby, binary logistic regression models (see Equation (1)) are well suited to analyse the factors influencing new venture creation and are specified below:

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \tag{1}$$

The independent variables used in the models were described in Section 3.1. As Table A1 illustrates (see Appendix A), significant correlations exist between some independent variables; however, these are rather weak and should not be an issue for subsequent modelling.

Additionally, this paper focuses on youth entrepreneurship, which can be included in the models by either splitting the dataset into younger (18–24) and older (25–64) individuals and fitting models for each, or by including a binary indicator of a person's age group as an independent variable within an overall model. Therefore, a total of seven models, as described in Table 2, is included in this study. Please note that throughout the paper we refer to the models by their respective model number, as indicated in Table 2, i.e., the same model maintains the same number in all tables of Section 3.

Before analysing any final model, the underlying dataset contains a few particularities that need to be addressed. By pooling data from 10 years of data collection (2009–2018), the sample size was increased to 46,937 cases, facilitating a sufficient number of observations, especially among young entrepreneurs. However, since TEA is a rare event, with only 6.1% of the respondents being involved, the model may not be ideal for predictions on unknown data but rather for statistical inferences on the underlying dataset. Furthermore, due to the extended timeframe of 10 years, during which the data was collected, the year of data collection may have an effect, be it fixed or random. Although globally impactful events such as COVID-19 were not observed during these years, the data were evaluated for such effects regardless. First, to include the survey year as a fixed effect, a dichotomous indicator for each survey year was generated. Each model described in Table 2 was then fitted with and without these variables. Although indicators for single years occasionally became significant, subsequent analysis of variance (ANOVA), documented in Table A2 (see Appendix A), as well as a comparison of the goodness-of-fit as indicated in the McFadden's R^2 and the AIC did not reveal meaningful explanatory power in the survey year. Considering this, it was deemed to be of little relevance as a fixed effect in the subsequent models.

Table 2. Model variants.

Model Number	Included Independent Variables	Included Data
1	Youngornotyoung	All
2	Person-related variables + youngornotyoung	All
3	Person-related variables + context-related variables + youngornotyoung	All
4	Person-related variables + youngornotyoung	Only Young
5	Person-related variables + context-related variables + youngornotyoung	Only Young
6	Person-related variables + youngornotyoung	Only Not Young
7	Person-related variables + context-related variables + youngornotyoung	Only Not Young

Second, a null two-level model with the survey year included as the Level 2 random effect was evaluated in comparison to a null single-level model without random effects, with little variance between the years being observed. Extending the full models by a Level 2 random effect (survey year) and calculating the intraclass correlation coefficients (ICC) as illustrated in Table A3 (see Appendix A) further confirms the lack of variance across years and thus does not warrant inclusion of random effects. Furthermore, when comparing the AIC, little improvements of mixed-effects models over fixed-effects models could be determined.

Third, each model was executed for each year individually, with the results being comparable and therefore robust with the model. Overall, it can be concluded that the survey year does not have a relevant influence on the model outcome.

To further evaluate the model results, each model was tested for multicollinearity (Table A4—see Appendix A) and goodness-of-fit (Hosmer–Lemeshow test; McFadden's R^2) as well as outliers in the deviance residuals and leverage. Multicollinearity was deemed to be a non-issue and assessed by means of the Generalized Variance Inflation Factor (GVIF) as presented by Fox and Monette (1992). Additionally, as illustrated in Table A5 (see Appendix A), the one-dimensional GVIF ($GVIF^{\frac{1}{(2*Df)}}$) does not exceed the threshold of $\frac{1}{1-R^2}$ (Vatcheva and Lee 2016) except on interaction terms, which is to be expected.

Outliers in deviance residuals remained acceptable, with the maximum peaking at 3.32 and the minimum at −1.19 at the tail ends. Outliers in leverage were compared to the model variant when excluded, and the influence was deemed low. Conclusively, no observations were excluded from the dataset in the final models. Furthermore, the models were compared to their respective null-models, with each being significantly better. Beyond fitting the models year-by-year, several measures to ensure robustness were undertaken. Given the rarity of entrepreneurship in Germany, the dependent variable is imbalanced. Therefore, the models may suffer from small sample bias, as described by King and Zeng (2001), although the imbalance is less prevalent in the dataset used for this study. To investigate this, a penalized likelihood logistic regression (Firth 1993; Heinze and Schemper 2002) was fitted for each of the models and compared to the unadjusted logistic regression outputs. Only miniscule deviations could be observed; therefore, small sample bias was deemed a non-issue. In addition, each model was evaluated against a probit model of identical specification, with the logit model performing slightly better, although with overall comparable results. Evaluating the models further, the rarity of entrepreneurship impedes procedures such as K-Fold cross-validation. There are, however, ways, to reduce this imbalance to receive accurate results. Consequently, K-Fold cross-validation with 10 folds and 10 repetitions was performed, using the 'Synthetic Minority Oversampling Technique' (SMOTE) as well as 'Random Over-Sampling Examples' (ROSE). Both yielded similar accuracy measures for the models, as showcased in Table A6 (see Appendix A) and generally exhibited low variability. Additionally, Table A6 also provides the mean area under the ROC curve (AUC) after randomly splitting the dataset into training and testing data (80% training to 20% testing ratio) 100 times and applying the models. Dispersion remained low and the models of this paper achieve acceptable (0.7–0.8) to excellent (0.8–0.9) discrimination, with only Model 1 being inadequate (Hosmer et al. 2013).

Overall, the models do not exhibit any issues and provide a McFadden's R^2 of up to 0.2. While some residuals can certainly be considered outliers, their overall effect on the model is low and the median of the residuals is close to zero.

4. Empirical Results

4.1. Descriptive Results

Before proceeding with the multivariate analysis, Figures 2 and 3 provide first descriptive information on the TEA of young people in Germany. Figure 2 illustrates the development of the TEA rate of both younger and older people over 23 years 2001–2022 for which these data are available in Germany. In most years, and on average over the whole period, the TEA rate of 18–24-year-olds is lower than that of 25–64-year-olds. However, this is different in individual years, with obvious differences between the two age categories. It should be noted that over this relatively long period, both global and national contexts can change, which can influence start-up activities as well as age-cohort-specific TEA rates. For example, as Figure 2 shows, the TEA rate of younger people was relatively and absolutely high during the new economy boom at the beginning of this millennium. The global economic and financial crisis of 2008/2009 had a negative impact on the start-up rate in many countries, but not Germany (Hundt and Sternberg 2014). The COVID-19 pandemic (from 2020 to 2022) had a profound impact on TEA rates in Germany (and other high-income countries): in the first year of the pandemic, after rising steadily in the years before the pandemic, TEA rates fell sharply, only to recover shortly afterwards and reach an all-time high for Germany in 2022 (Fritsch et al. 2021; Sternberg et al. 2022; GERA 2023).

As for our paper, important independent variables are only available for 2009–2018; thus, the multivariate analysis in our paper is limited to this period.

Figure 3 shows the mean TEA rates for our study period from 2006 to 2018, as well as the exact age cohorts (age at the time of the survey). Overall, the figure confirms the observations of many other countries, and Germany as well, that entrepreneurial activity across age shows an approximately inverted U-shaped course, i.e., the very young and very old cohorts have lower TEA rates than the middle-aged cohorts. A comparison with Figure 2 suggests that this inverse U-curve would be somewhat flatter if the entire period for which GEM data are available in Germany (2001–2022) was used. Especially at the beginning of this millennium and during the COVID-19 pandemic, the TEA rates of 18–24-year-olds in Germany were high in absolute and relative terms (compared to the TEA rates of 25–64-year-olds).

Figure 3 also shows that the 18–24 age group is relatively heterogeneous in terms of TEA rates. It ranges from 3.8% for 18-year-olds to just under 6.5% for 24-year-olds and increases with age (but not for each cohort), although not steadily. Within this context, a note on the statistical representativeness of the GEM data was used. In our sample, 18–24-year-olds account for 10.8% of all 18–64-year-olds interviewed (or 5060 of the 46,937 persons interviewed). For the individual cohorts of 18–24-year-olds, there are between 662 cases (for the 20-year-olds, 1.4% of the total sample) and 766 cases (for the 24-year-olds, 1.9% of the total sample). These percentages are sufficiently close to the corresponding figures for Germany as a whole. According to the German Statistical Office (Statistisches Bundesamt [German Statistical Office] 2023), in the year 2018, a total of 10.4% of 18–64-year-olds were between 18 and 24 years old. This value deviates only slightly from the above-mentioned reference value of our sample (10.8%). Even for the seven individual cohorts of 18–24-year-olds, the differences between the sample and population are never higher than 0.12 percentage points.

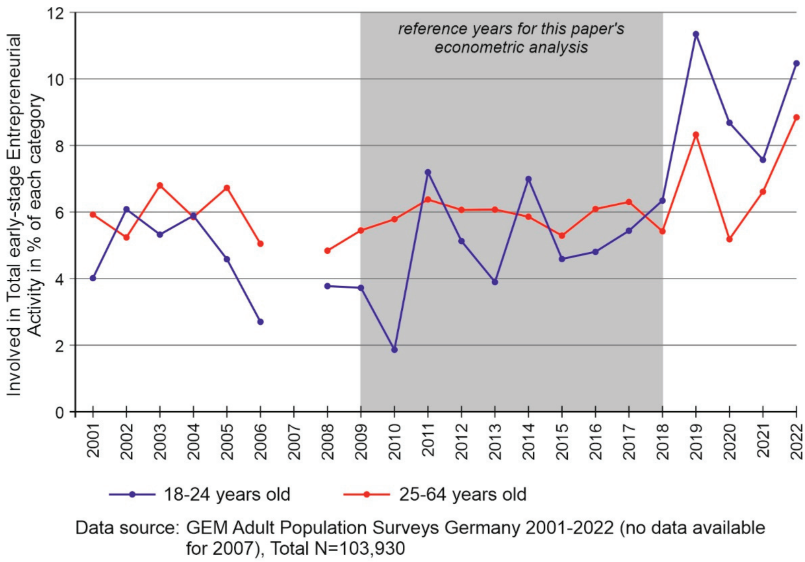

Figure 2. Annual TEA rates by age categories in Germany 2011–2022.

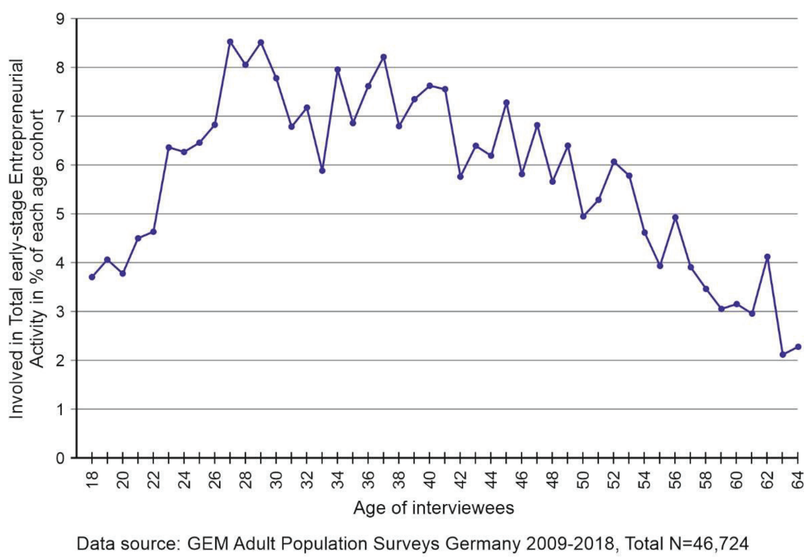

Figure 3. TEA rates by age categories in Germany 2009–2018.

Before we deal with the test of the five hypotheses using logistic regression models in the next chapter, we present another important descriptive result in Table 3, namely the comparison of founders and non-founders, each differentiated according to the two age categories. It is quite clear that the young founders are much more often male, have a lower household income and are less convinced of their entrepreneurial skills than the older founders. In contrast, there are no statistically significant differences between younger and older founders in terms of the fear of failure as a barrier to founding, the level of formal education and business angel activity. Both subpopulations differ significantly in two of the four contextual factors: young founders recognize more respect for successful founders in German society and view the start of their own business as an attractive career option compared to the older founders. When comparing young founders with young non-founders, the expected higher values for founders emerge, for example, in the assessment of founding skills and entrepreneurial opportunities in the knowledge of other entrepreneurs and household income. The significantly higher proportion of men among the founders is also to be expected. In contrast, both subgroups of young men do not differ in their assessment of the status and respect of founders in society. The significantly more frequent significant coefficients in the group of non-founders, on the other hand, should not be overinterpreted, as they are at least partially due to the significantly larger number of cases compared to the founders.

Table 3. Characteristics of founders and non-founders compared by age.

Founders	**Mean Young**	**Mean Not Young**	**Pearson's X^2**	**Sig**
Person-related factors				
Businessangel	0.10	0.10	0.00	
Education	0.92	0.91	0.20	
Fearoffailure	0.17	0.20	1.50	
Gender	0.24	0.38	16.15	***
HHIncome (annual, 1000 €)	26,618.23	31,611.57	15.51	***
Skills	0.67	0.87	61.97	***
Context-related factors				
Career	0.63	0.44	30.84	***
Goodopp	0.58	0.63	1.67	
Knowent	0.62	0.66	1.45	
Respect	0.79	0.71	6.35	**
Non-founders				
Person-related factors				
Businessangel	0.03	0.04	16.58	***
Education	0.89	0.83	102.96	***
Fearoffailure	0.39	0.47	91.91	***
Gender	0.45	0.50	38.38	***
HHIncome (annual, 1000 €, categories)	18,372.34	25,195.37	406.31	***
Skills	0.20	0.44	975.48	***
Context-related factors				
Career	0.64	0.47	417.67	***
Goodopp	0.40	0.38	8.02	***
Knowent	0.27	0.26	2.00	
Respect	0.84	0.78	86.47	***

Note: ** $p < 0.05$, *** $p < 0.01$.

4.2. Regression Models

Table 4 illustrates the results of the first three models with *all* observations, regardless of age included in the underlying dataset. The odds ratios are mostly in line with the hypothesized outcomes. However, some reveal striking implications. Fear of failure seems to be a major deterrent to starting a business, while confidence in the skills and knowledge of an entrepreneur are major drivers of TEA. Remarkably, household income has a negative effect if it is larger than two-thirds of the population, but it shows no impact otherwise. Additionally, the lower likelihood of starting a business as an older entrepreneur is revealed. However, when this interacted with gender, it can be observed that women are more likely to start a business at an older age, while men usually do so earlier in life. In any case, age plays an important role in the probability of founding a company, which subsequently legitimizes several of our hypotheses. This also applies to the strong influence of skills, even independent of the age of the respondents. The R^2 increases noticeably if the contextual factors are also taken into account in Model 3 in addition to the person-related factors. When comparing Models 2 and 3, most of the odds ratios remain stable and statistically significant after adding the four contextual factors (three of which are themselves significant).

Table 4. Factors affecting the decision to start a business in total population.

Independent Variables	Model 1 Odds Ratios	Model 2 Odds Ratios	Model 3 Odds Ratios
Person-related factors			
Businessangel (1 = yes, 0 = no)		1.600 *** (0.08)	1.104 (0.086)
Education (1 = yes, 0 = no)		1.632 *** (0.082)	1.440 *** (0.091)
Fearoffailure (1 = yes, 0 = no)		0.400 *** (0.056)	0.455 *** (0.063)
Gender (1 = female, 0 = male)		0.542 *** (0.18)	0.584 *** (0.193)
Youngornotyoung (1 = not young, 0 = young)	1.241 *** (0.069)	0.588 *** (0.097)	0.593 *** (0.105)
Youngornotyoung # Gender (not young.female)		1.557 ** (0.186)	1.502 ** (0.201)
HHIncome (lowest 33% tile) (1 = yes, 0 = no)		0.947 (0.063)	0.977 (0.07)
HHIncome (highest 33% tile) (1 = yes, 0 = no)		0.977 (0.054)	0.844 *** (0.061)
Skills (1 = yes, 0 = no)		6.268 *** (0.062)	4.468 *** (0.069)
Context-related factors			
Career (1 = yes, 0 = no)			0.993 (0.053)
Goodopp (1 = yes, 0 = no)			1.64 *** (0.054)
Knowent (1 = yes, 0 = no)			3.481 *** (0.055)
Respect (1 = yes, 0 = no)			0.793 *** (0.06)
Intercept	0.05 *** (0.066)	0.031 *** (0.130)	0.026 *** (0.156)
Goodness-of-fit			
R^2	0.00	0.13	0.18
Hosmer-Lemeshow Sig.	-	0.37	0.77
Observations	46,724	33,809	24,609

Note: ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. # means interaction term.

In the second set of models (Table 5), the sample was divided into 'young' (Models 4 and 5) and 'not young' individuals (Models 6 and 7), and Models 2 and 3 were applied again. Generally, the results of Model 2 and 3 can be confirmed; however, some nuances become visible. For one, formal education seems to be of little relevance in younger entrepreneurs but strongly significant in older founders. Opportunity recognition is more relevant for older entrepreneurs, while having a higher income remains a deterrent.

Table 5. Factors affecting the decision to start a business among 18–24 aged vs. 25–64 aged.

Independent Variables	Model 4 Odds Ratios	Model 5 Odds Ratios	Model 6 Odds Ratios	Model 7 Odds Ratios
Person related factors				
Businessangel (1 = yes, 0 = no)	1.529 (0.275)	1.116 (0.287)	1.605 *** (0.084)	1.099 (0.091)
Education (1 = yes, 0 = no)	1.284 (0.291)	1.100 (0.304)	1.673 *** (0.085)	1.478 *** (0.096)
Fearoffailure (1 = yes, 0 = no)	0.341 *** (0.207)	0.355 *** (0.219)	0.403 *** (0.059)	0.465 *** (0.066)
Gender (1 = female, 0 = male)	0.585 *** (0.184)	0.625 ** (0.198)	0.839 *** (0.051)	0.873 ** (0.057)
HHIncome (lowest 33% tile) (1 = yes, 0 = no)	0.837 (0.199)	0.922 (0.214)	0.969 (0.066)	0.996 (0.075)
HHIncome (highest 33% tile) (1 = yes, 0 = no)	1.283 (0.199)	1.220 (0.214)	0.959 (0.056)	0.819 *** (0.064)
Skills (1 = yes, 0 = no)	7.076 *** (0.164)	5.373 *** (0.175)	6.156 *** (0.067)	4.357 *** (0.075)
Context related factors				
Career (1 = yes, 0 = no)		1.057 (0.177)		0.985 (0.056)
Goodopp (1 = yes, 0 = no)		1.207 (0.171)		1.704 *** (0.057)
Knowent (1 = yes, 0 = no)		2.944 *** (0.177)		3.539 *** (0.058)
Respect (1 = yes, 0 = no)		0.931 (0.22)		0.782 *** (0.062)
Intercept	0.035 *** (0.333)	0.031 *** (0.414)	0.018 *** (0.106)	0.015 *** (0.133)
Goodness-of-fit				
R^2	0.17	0.20	0.12	0.18
Hosmer-Lemeshow Sig.	0.99	0.92	0.25	0.93
Observations	3086	2303	30,723	22,306

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Table 5 provides all the results needed to decide on our five hypotheses. None of the 10 independent variables examined in the models has a stronger influence on the TEA variable than the perception of one's own entrepreneurial skills. This is true for each of the Models 4–7, i.e., for both younger and older people. The probability that the respondent will start a business is between four and six times higher for a person who believes that they have the necessary skills to start a business than for those who do not. The odds ratios are even higher for younger people than for older people. Comparing the models (Models 5 and 7) with and without the contextual variables (Models 4 and 6), the odds ratios are only slightly reduced for the former. Overall, this results in a very convincing confirmation of Hypothesis 1.

In all models, women show a lower probability of starting a business than men, regardless of age. However, in each of the four models (as well as Models 2 and 3 in Table 4), the statistically highly significant odds ratios for older women are less far removed from those of (older) men than is the case for younger women. Thus, women start businesses less often and later in life than men. Hypothesis 2 must therefore be rejected.

If a respondent might not start a business because of the fear of failure, this reduces the actual probability of starting a business by approximately 65% for younger people and by only 55% for older people, compared to people who do not have this fear of failure. These odds ratios are also statistically significant in all models. Due to the proven (although not very significant) differences between the impact on younger and older people (stronger for the former), we consider Hypothesis 3 to be mainly not confirmed.

For young people, the four variables regarding their own perception of the entrepreneurial environment factors are not statistically significant in three out of four cases, and only the odds ratios of knowing another entrepreneur are high and significant. Among the older respondents, on the other hand, the odds ratios of these contextual factors are significant in most cases. The positive evaluation of entrepreneurial opportunities and the acquaintance of another entrepreneur are the variables with the 3rd and 2nd strongest influence of all 10 independent variables among older people. We can therefore consider Hypothesis 4 to be confirmed.

For both older and younger people, knowing another entrepreneur (who has founded a business in the last two years) significantly increases their probability of founding a business. It is 2.9 times higher for younger people and 3.5 times higher for older people than for people who do not know such entrepreneurs personally. The difference between the two age categories is noticeable, although not very large. We can thus essentially confirm Hypothesis 5.

In addition to these results concerning the five hypotheses, the regression models show another interesting finding. For older people, a high level of formal education increases the probability of founding a business by a factor of 1.5 to 1.7 (compared to people with a lower level of education), while no statistically significant influence can be found for younger people.

5. Discussion of Results

Our empirical findings documented in Chapter 4 show two results. First, young people differ considerably from older people in terms of the likelihood of starting a business and, in particular, the factors that explain this likelihood. While the lower likelihood of younger people compared to older people (especially the middle-aged cohorts), which we also identified, has been shown before, at least for most high-income countries (e.g., Schøtt et al. 2015), this paper makes an important contribution to the explanatory factors of these differences, differentiated according to person-related and contextual factors. This is not found in previous literature and data for an entire country. To the best of our knowledge, however, this paper is the first to examine these factors by differentiating between younger and older people in Germany. Second, the empirical findings show that young founders also differ considerably from young non-founders in terms of important demographic characteristics and the assessment of the entrepreneurial context. For most of our 10 independent variables, these intragenerational differences are similar to those of older people (especially for gender and entrepreneurial skills). Both core results justify a specific consideration of young people in the analysis of start-up frequencies and their factors for selected countries or subnational regions. In other words, one should not assume that an analysis of these factors for a country and all adults will adequately reflect start-up behaviour and its factors for younger people.

Of the five hypotheses tested, three could be confirmed without limitations and two could not. Overall, this attests to an appropriate and open-ended analysis strategy, albeit with limitations, as discussed in Section 5. Our analysis of Hypothesis 1 shows that the positive perception of one's own entrepreneurial skills is not only a significant factor in young people's decision to start a new business but also the one with the highest odds ratios of all 10 independent variables in all relevant regression models. The odds ratios for this variable are all positive and statistically significant, and they show that young people with a positive self-perception are between five and seven times more likely to start a business than those who do not have this positive perception. This confirms the findings of Schøtt et al. (2015) and Hekman (2007), even if they do not explicitly refer to young people in Germany or to the aforementioned self-efficacy in entrepreneurial skills. However, the sources mentioned do not examine the impact of this self-efficacy on the actual decision to start a business. To our knowledge, our analysis is the first to illustrate the significance of the perception of one's own entrepreneurial skills explicitly for young people in Germany and in relative terms compared to older people.

Hypothesis 2 is not supported by our models. Contrary to expectations, the start-up frequency and factors in men already differ from women at a young age and not only when they are older. In fact, women do not completely catch up with men in terms of start-up activities at an older age, but they do at least partially. There must therefore already be person-related and/or contextual factors at a young age that cause young women to start businesses much less often than men. Our interaction term of the dummy variable age category (young–old) and gender shows a 1.5 times higher probability for women between the ages of 25 and 64 than for other people. This confirms recent—purely descriptive—statements of the GEM Women Report, according to which the ratio of TEA start-ups by women compared to men in Germany in 2021 is about 0.8 for 18–24-year-olds but 1.2 and 1.1 for 24–54-year-olds and 55–64-year-olds, respectively (GEM 2022). If the gender gap in start-ups is to be reduced, it is therefore necessary—also in Germany—to start doing so in the first two to three decades of young people's lives.

Our core argument in connection with the variable 'fear of failure as a reason not to start a business' was life and work experience, of which younger people naturally have less than older people. Younger people have not yet had as many negative experiences of failure and therefore cannot have had as many (negative) experiences with social consequences of individual failure as older people, which is, we assumed, why they are less likely to refrain from starting a business, that is, because they fear the social or other consequences of a failed start-up (but for other reasons). The result is therefore quite surprising, as many studies show that because older people can lose more on average through a risky start-up than younger people, risk aversion is therefore higher among older people (Schøtt et al. 2015; Mather et al. 2012). Apparently, there are other factors (not covered in the canon of our independent variables) associated with the fear of failure variable that explain why younger people are more influenced by the fear of failure than older people. Conceivable factors are a fundamentally lower self-efficacy (which we actually observed in relation to entrepreneurial skills in Hypothesis 1) or a fundamentally more pessimistic view of the future among younger people (i.e., those who were younger earlier) in view of many medium- or long-term crises (pandemic, climate change, etc.).

For young people, the contextual factors studied have less influence on the start-up decision than personal factors than for older people (Hypothesis 4). For some contextual factors, this is more than plausible and confirms older findings. For example, the two person-related factors of gender and self-efficacy in entrepreneurial skills have a significant influence on the start-up decision in general, but this influence is stronger for younger people than for older people. The network and role model variable investigated in Hypothesis 4 is the only one with a strong effect on the start-up decision among younger people, unlike among older people, for whom three of the four contextual variables exert a strong influence. We interpret this in the sense that younger people, due to less professional and life experience, know and assess their own person (relatively) better than the (spatial and other) context. For older people, on the other hand, it tends to be the other way round. This greater ability to assess personal factors leads to the latter being given greater weight in such an important decision in favour of or against an entrepreneurial career than is the case with older people. In our opinion, this comparison of a total of 10 factors in the same regression models and with concrete reference to a country—and on an empirically sufficient basis—is one of the important contributions that our paper makes to the literature. For young people, the context (here especially related to the regional context) is less important than for older people. The widespread postulate in regional entrepreneurship research that the regional environment is an important cause of the start-up decision and subsequent start-up success (e.g., Dahl and Sorenson 2012) may therefore apply more to older than younger entrepreneurs.

As the analysis of Hypothesis 5 has shown, the acquaintance of another entrepreneur has a strong and positive influence on the probability of founding a company. This influence is present for both younger and older people, but it is even stronger for the latter, as expected. We interpret this finding in the light of the role model argument (Fritsch and Wyrwich 2018; Wyrwich et al. 2019). According to this, there is both a positive and a negative side to role models. If the entrepreneur with whom our respondents are acquainted has had good experiences with their start-up (e.g., founded very successfully and/or experienced great satisfaction in this type of gainful employment), then this could have a positive effect on their acquaintance and entrepreneurial intention ('if they can do it, I can, too' (Sorenson and Audia 2000, p. 443). Conversely, negative experiences can have the opposite effect on the acquaintance ('if they can fail, I can, too'). It is possible that younger people have more frequent contact with successful entrepreneurs than failed entrepreneurs—or that their perception of (successful and failed) founders in the media they use (possibly different from those used by older people) conveys a more positive image of entrepreneurs (Tubadji et al. 2021). In any case, the analysis shows for both age categories a clear confirmation of the impact of role models and network relationships with actual founders on the decision to found a company, which has previously been studied for Germany (see Brüderl and Preisendörfer (1998) on the network hypothesis for new firm founders in general) but without reference to age.

6. Implications for Policy and Further Research

The core results of the paper can be summarized as follows. First, young people differ considerably from older people in terms of the likelihood of starting a business and, in particular, the factors that explain this likelihood. Second, young founders differ considerably from young non-founders in terms of demographic characteristics (gender, household income, entrepreneurial skills) and the assessment of the entrepreneurial context (e.g., perception of entrepreneurial opportunities). For most of our 10 independent variables, these intragenerational differences are similar to those of older people (especially for gender and entrepreneurial skills). Third, the positive perception of one's own entrepreneurial skills is not only a significant factor in young people's decision to start a business, but also the one with the highest odds ratios of all ten independent variables in all relevant regression models. Fourth, men's likelihood of starting a business already differs from women at a young age. In fact, women do not completely catch up with men in terms of start-up activities at an older age, but they do catch up at least partially. Fifth, young people are *not* less likely than older people to refrain from starting a business because they fear the social or other consequences of a failed start-up (but for other reasons). Sixth, for young people, the contextual factors studied have less influence on the decision to start a business than the person-related factors as compared to older people. Finally, the acquaintance of another entrepreneur has a strong and positive influence on the probability of founding a company. This influence is present for both younger and older people, but it is even stronger for the latter.

These empirical results for Germany, the focus of the paper, give rise to several implications for start-up policy. If the goal of government policy is to generate the (mostly positive) economic effects of a high national entrepreneurship rate (Fritsch 2013), the relatively low start-up rate in Germany must increase. It is rational to start politically with those population groups whose start-up rates have been comparatively low so far, such as those of younger people. Even if not all of these policies generate the desired economic effects (Shane 2009) and only relatively few public policy programmes to assist new youth businesses are evaluated by independent and neutral researchers (cf. OECD 2023), such tax-funded policies are comparatively inexpensive and more sustainable attempts to support economic development and, in particular, regional structural change through the regular renewal of the business stock compared to efforts to promote large, old and established companies in Germany or even abroad. However, the great heterogeneity of new businesses must explicitly be taken into account (Minniti 2008).

The empirical results of the paper provide evidence for such entrepreneurship support policies in favour of younger people (Mariani et al. 2019). We argue that such policies should, if possible, explicitly address the empirically proven factors involved in youth entrepreneurship; in other words, no 'one size fits all' policy for new businesses, regardless of the age of the founders. Policymakers still too often develop programmes that are intended to appeal to all founders—and thereby unintentionally disadvantage the much more numerous older founders of new businesses. To develop good start-up policies for young people, one must know their motives and framework conditions and then develop suitable policy instruments. The various 'inclusive entrepreneurship' reports of recent years for Germany (OECD and European Commission 2021) show that, despite some efforts, there remains room for improvement, also in comparison with other countries. For younger people (defined in the paper as 18–24-year-olds) in Germany, self-efficacy in entrepreneurial skills, personal acquaintance of other entrepreneurs and fear of the social consequences of failure in a new business is particularly important when deciding to start their own businesses or not. In contrast, the formal educational status and the reputation of successful founders in society do not play an important role, which is quite different from older people. Policy measures in favour of new businesses of younger people should therefore aim to improve the entrepreneurial skills of this target group, which is naturally easier and earlier within the context of school education. However, for many years, and despite several initiatives, this has been a comparative weakness of the entrepreneurial context in Germany compared to other countries, as the annual GEM Country Report Germany has documented for many years (for the most recent one, see Sternberg et al. (2022)). The fear of failure as a start-up barrier—as a social phenomenon—is less easy (or even quick) to influence through start-up policy measures, while the personal acquaintance of other founders is not at all.

Of course, this paper also has some limitations. With a total of 10 independent variables, we have attempted to take into account both important person-specific and contextual factors. However, factors such as migration background or place of residence within Germany had to be omitted. This is especially true for some contextual factors (e.g., economic framework conditions). The number of cases, although higher in the GEM data set for Germany than any other country (apart from the UK and Spain) and other surveys worldwide, would have had to be even higher in individual years to be able to adequately conduct the very detailed logit regressions that require large samples. Therefore, we had to reduce the data analyses planned for the period 2001–2022, with more than 100,000 cases, to 2009–2018 (with a good 46,000 cases). Finally, it should be noted that our entire analysis focuses on young people in Germany as a whole, although interregional differences within Germany (as in most countries) in the start-up behaviour and attitudes of young men and women are likely (for example, between West and East Germany or between urban and rural regions).

The paper and the data used in it offer numerous opportunities for further research. In part, the corresponding topics can also be covered with (already existing) GEM data, but we have gone beyond the scope of this paper. This applies, for example, to the distinction between positive and negative role model effects or the influence of the pandemic (or other external shocks) on the self-efficacy for entrepreneurial skills—and thus on new businesses—among young people. The interregional differences in young people's entrepreneurial behaviour mentioned under limitations would also be worth including in the analysis from the perspective of young people in the future. The data from the annual GEM Adult Population Survey would also allow this in principle.

Data from sources other than GEM could enrich the analysis, especially for contextual factors (e.g., by adding economic or social characteristics of the region in which the person lives). Not only the start-up decision itself but also the factors of the subsequent success of the new business would be worth considering. They are potentially even more important in the economic effects desired by start-up policy than the decision to start a new business. The GEM also offers some data for these success characteristics (e.g., on the expected employment or turnover effects and export intensity).

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Abbreviations

ANOVA	Analysis Of Variance
APS	Adult Populations Survey
GEM	Global Entrepreneurship Monitor
GVIF	Generalized Variance Inflation Factor
ICC	Intraclass Correlation Coefficients
OECD	The Organization for Economic Cooperation and Development
ROSE	Random Over-Sampling Examples
SMOTE	Synthetic Minority Oversampling Technique
TEA	Total early-stage Entrepreneurial Activity
UN	United Nations

Appendix A

Table A1. Pearson correlation coefficients of independent variables.

	Gender	HHIncome	Education	Busangel	Skills	Fearoffailure	Goodopp	Career	Respect
Gender									
HHIncome	−0.09 ***								
Education	0.05 ***	0.21 ***							
usangel	−0.06 ***	0.09 ***	0.04 ***						
Skills	−0.16 ***	0.17 ***	0.08 ***	0.10 ***					
Fearoffailure	0.13 ***	−0.08 ***	−0.03 ***	−0.06 ***	−0.19 ***				
Goodopp	−0.09 ***	0.17 ***	0.12 ***	0.07 ***	0.13 ***	−0.12 ***			
Career	−0.01	−0.08 ***	−0.08 ***	−0.03 ***	−0.05 ***	−0.01 ***	0.03 ***		
Respect	0.04 ***	0.04 ***	0.05 ***	−0.02 ***	−0.08 ***	0.06 ***	0.07 ***	0.17 ***	
Knowent	−0.08 ***	0.12 ***	0.09 ***	0.16 ***	0.22 ***	−0.09 ***	0.17 ***	−0.01 *	−0.03 ***

Note: * $p < 0.1$, *** $p < 0.01$.

Table A2. Deviance of survey year and its significance in ANOVA.

Year	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
2010	0	15 ***	73 ***	5 **	13 ***	12 ***	61 ***
2011	5 **	1	19 ***	1	5 **	1	16 ***
2012	3	2	6 **	1	3 *	2	4 *
2013	1	0	7 ***	0	0	0	8 ***
2014	1	0	0	8 ***	5 **	0	2
2015	1	1	3 *	1	2	0	2
2016	0	1	0	0	0	1	0
2017	2	0	5 **	0	1	0	5 **
2018	1	5 **	17 ***	0	1	5 **	17 ***

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3. Summary of intraclass correlation coefficients (ICC).

Model Number	ICC
1	0
2	0.003
3	0.028
4	0.011
5	0.045
6	0.002
7	0.027

Table A4. One-dimensional generalized variance inflation factors and R^2 threshold.

Variable	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Businessangel	1.01	1.016	1.015	1.025	1.009	1.015
Education	1.019	1.022	1.011	1.017	1.02	1.022
Fearoffailure	1.012	1.019	1.009	1.013	1.013	1.022
Gender	3.756	3.59	1.02	1.022	1.018	1.022
HHIncome	1.02	1.024	1.011	1.016	1.017	1.023
Skills	1.033	1.049	1.009	1.025	1.02	1.031
Career		1.029		1.013		1.024
Goodopp		1.027		1.013		1.03
Knowent		1.03		1.032		1.031
Respect		1.026		1.018		1.027
youngornotyoung	1.186	1.195				
youngornotyoung # Gender	3.837	3.671				
R^2 Threshold	1.145	1.215	1.205	1.251	1.14	1.212

stands for interaction terms.

Table A5. Generalized variance inflation factors.

Variable	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Businessangel	1.02	1.03	1.03	1.05	1.02	1.03
Education	1.04	1.04	1.02	1.03	1.04	1.05
Fearoffailure	1.02	1.04	1.02	1.03	1.03	1.04
Gender	14.11	12.89	1.04	1.04	1.04	1.04
HHIncome	1.08	1.1	1.05	1.07	1.07	1.09
Skills	1.07	1.1	1.02	1.05	1.04	1.06
Career		1.06		1.03		1.05
Goodopp		1.06		1.03		1.06
Knowent		1.06		1.06		1.06
Respect		1.05		1.04		1.05
youngornotyoung	1.41	1.43				
youngornotyoung # Gender	14.72	13.48				

stands for interaction terms.

Table A6. Area under ROC curve and K-Fold Cross Validation Accuracy.

Model	Measure	Mean	SD
Model 1	AUC	0.5107	0.0059
Model 1	K-Fold Cross Validation (SMOTE)	0.1554	0.0045
Model 1	K-Fold Cross Validation (ROSE)	0.1711	0.1109
Model 2	AUC	0.7698	0.0096
Model 2	K-Fold Cross Validation (SMOTE)	0.6724	0.0088
Model 2	K-Fold Cross Validation (ROSE)	0.6707	0.0083
Model 3	AUC	0.8109	0.0103
Model 3	K-Fold Cross Validation (SMOTE)	0.7236	0.0099
Model 3	K-Fold Cross Validation (ROSE)	0.7198	0.0096
Model 4	AUC	0.7988	0.0358
Model 4	K-Fold Cross Validation (SMOTE)	0.7968	0.0343
Model 4	K-Fold Cross Validation (ROSE)	0.7854	0.0336
Model 5	AUC	0.8094	0.0334
Model 5	K-Fold Cross Validation (SMOTE)	0.7585	0.0254
Model 5	K-Fold Cross Validation (ROSE)	0.752	0.0275
Model 6	AUC	0.7662	0.009
Model 6	K-Fold Cross Validation (SMOTE)	0.6591	0.0085
Model 6	K-Fold Cross Validation (ROSE)	0.659	0.0107
Model 7	AUC	0.8104	0.0101
Model 7	K-Fold Cross Validation (SMOTE)	0.7247	0.0113
Model 7	K-Fold Cross Validation (ROSE)	0.7172	0.0105

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When an Exchange Semester Is No Longer Enough: Why and How the Bologna-Reforms Changed the Behavior of High-Ability Students?

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Abstract: Emphasizing the existence of information asymmetries between, e.g., young academics and potential employers, signaling theory has shaped our understanding of how high-ability students try to document their superior skills in a competitive environment such as the labor market: high-ability individuals benefit from a relative cost advantage compared to low-ability individuals when producing a credible signal of superior ability. When this cost advantage decreases, the signal's value also decreases. We analyze how the signal 'international qualification' has changed due to increasing overall student mobility, driven by the effect of a massive change in the institutional framework, namely the implementation of the Bologna reforms. Using a large and hitherto not accessible dataset with detailed information on 9096 German high-ability students, we find that following the Bologna reforms, high-ability students extended their stays and completed degrees abroad (instead of doing exchange semesters). No such changes in behavior are to be observed in the overall student population. We conclude that completing a degree abroad is the new labor market signal for the 'international qualification' of high-ability students.

Keywords: educational economics; signaling theory; international student mobility; degree mobility; high-ability students; Bologna reforms

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1. Introduction

1.1. Labor Market Signaling

The labor market is traditionally characterized by information asymmetries between employers trying to recruit the most productive job candidates and job seekers competing for highly paid entry positions. According to Spence (1973), high-ability individuals will, therefore, produce a signal to distinguish themselves from low-ability individuals and thereby improve their labor market position. Each signal serves as an indicator for employers to identify individuals who are more productive and, thus, more attractive as potential future employees. However, a signal is credible if only high-ability individuals are willing to produce it while its production is too costly for low-ability individuals who will, therefore, refrain from investing in its production (Spence 1973).

Previous evidence has shown that with the general expansion of higher education (Schofer and Meyer 2005) signals, such as the completion of a tertiary degree, are no longer credible as their exclusiveness has disappeared. Hence, other signals, where high-ability individuals can still profit from their lower relative cost in producing it, became relevant. While Frick and Maihaus (2016) found internships in prestigious companies to be a credible labor market signal, others have identified international qualifications, i.e., an exchange semester abroad, as another relevant labor market signal (Messer and Wolter 2007; Relyea et al. 2008; Netz and Finger 2016).

However, just as higher education, in general, has lost its signaling effect due to its decreasing exclusiveness, the broad increase in international student mobility (e.g., in the form of exchange semesters) in recent years (Teichler 2012; DAAD and DZHW 2020) may have resulted in a similar effect. For European students, one reason for this increase in international mobility can be associated with the Bologna reforms.

1.2. Bologna Reforms

The Bologna reforms refer to an initiative by 29 European countries[1] to form a coherent European Higher Education Area with harmonized structures. An according declaration was signed by the education ministers of the participating countries in 1999 at the University of Bologna. Concrete measures of the reforms were implemented in the respective countries' education systems subsequently (European Commission 2021; EHEA 2020).

The ultimate goals of the reforms were to "facilitate student and staff mobility, to make higher education more inclusive and accessible, and to make higher education in Europe more attractive worldwide" (European Commission 2021). The measures taken to achieve these goals include a harmonized education system consisting of three separate yet consecutive tiers (Bachelor, Master, and doctoral studies) and the mutual recognition of study efforts completed abroad (European Commission 2021; EHEA 2020).

Looking at these changes in the institutional framework from a signaling perspective, we hypothesize that barriers to international student mobility have been lowered and, thus, the cost of producing the signal of international qualifications was dramatically reduced for all students. More specifically, there is now less room for high-ability students to distinguish themselves from the overall student population.

Thus, we hypothesize that utility-maximizing high-ability students will shift their attention to alternative forms of international qualifications that still allow them to produce a credible labor market signal. Since a signal is credible only if its production is costly, high-ability students must enjoy a cost advantage compared to low-ability students. As a consequence, we expect a change in the mobility behavior of high-ability students due to the increasing overall student mobility driven by the implementation of the Bologna reforms.

2. Literature Review

2.1. Signaling Theory

According to signaling theory, high-ability individuals are interested in distinguishing themselves from low-ability individuals via the production of a credible signal that demonstrates their superior abilities. The latter will typically refrain from investing in the same signal because the production costs are too high for them. This underlying negative correlation between an individual's productivity and the cost of producing a signal makes signaling so relevant for employers who are typically seeking to recruit the most productive job candidates (c.f., Bills 2003; Spence 1973).

In the labor market, higher education is one such signal. By acquiring certain educational credentials, an individual can signal his/her abilities to prospective employers and increase his/her labor market prospects (c.f., Spence 1973; Löfgren et al. 2002). Recently, a number of empirical studies have demonstrated that specific higher education signals are, for example, an individual's grades relative to the overall student population (Tyler et al. 2000), internships in particularly prestigious companies (Frick and Maihaus 2016), and study stays abroad or, in general, international qualifications (Messer and Wolter 2007; Relyea et al. 2008; Netz and Finger 2016).

2.2. Existing Evidence on the Consequences of Studying Abroad on Labor Market Outcomes

A labor market signal indicating international qualifications can take various forms such as, e.g., an exchange semester, a research visit at a university in another country, or an academic degree acquired abroad. Students who invest in the production of such signals should, therefore, have better labor market prospects in the sense that they find jobs with better advancement opportunities and/or receive higher starting salaries than their peers who refrain from producing one (or more) of these signals.

A large body of literature has shown the positive effects of studying abroad on graduates' labor market prospects: Messer and Wolter (2007) surveyed 3586 Swiss university graduates and found indeed that participation in an exchange program is associated with higher starting salaries. Similarly, Kratz and Netz (2018) used panel data from two German graduate surveys (n_1 = 2719 and n_2 = 1511) and found that international student mobility is correlated with both steeper wage growth after graduation and higher medium-term wages, the latter being due to a higher probability of working in large multinational companies. Parey and Waldinger (2011) confirmed this pattern in their analysis that used survey results of n > 50,000 German university graduates from the years 1989, 1993, 1997, 2001, and 2005. They found that having studied abroad increases the probability of working in a foreign country by about 6–15 percentage points, depending on their model specifications. Using an experimental design, Petzold (2017) randomly sent out 231 applications with systematically varied CV information on having studied abroad and on professional work experience for internships offered by German employers. The most important result of this study is that having studied abroad has a significantly positive impact on, first, the response time of the respective employer and, second, the probability of receiving an invitation for a job interview, particularly from multinational firms.

Given these positive effects of an international qualification on a student's labor market prospects, we expect that utility-maximizing individuals will be motivated to invest in a study stay abroad or other forms of international experience (c.f., Petzold and Moog 2018; Relyea et al. 2008; Tomlinson 2008; Netz and Finger 2016).

However, the existing evidence also shows that this motivation to study abroad differs between different groups of individuals, depending on their field of study. Especially business and economics majors are motivated to use a study abroad signal to improve their labor market prospects. Toncar et al. (2006) found that business students are particularly well aware of the potential signaling effects of having studied abroad, emphasizing that such an experience will improve their labor market prospects. This is not surprising as one can expect that business and economics majors are familiar with the underlying concept emphasizing the costs of producing a signal and its relevance for potential employers.

2.3. Recent Developments of International Student Mobility

However, with the general expansion of (higher) education (Schofer and Meyer 2005), traditional higher education signals, such as an exchange semester spent abroad, may no longer be credible when the number of individuals that are able to produce a particular signal increase due to, e.g., a change in the institutional environment, the relative cost advantage to produce that signal decreases for high-ability individuals. This, in turn, makes the signal less valuable (Spence 1973). This is what happened to the signal "international qualification" in terms of spending one or two semesters at a university abroad[2]. Teichler (2012, p. 34), in his comprehensive analysis of international student mobility in the context of the Bologna reforms, concludes that the "*value of student mobility gradually declines as a consequence of gradual loss of exclusiveness*".

With the changes in the institutional framework for studying abroad, i.e., the implementation of the Bologna reforms, the cost of studying abroad decreased for all students. As a consequence, more students are now able to go abroad, and the exclusiveness of the previously highly appreciated signal of international qualification decreases. The costs of studying abroad can be monetary, e.g., travel costs or higher costs of living abroad, and non-monetary, e.g., language barriers or efforts to organize a stay abroad and integrate it into the home university's program (c.f., Petzold and Moog 2018; Doyle et al. 2010; Presley et al. 2010). Typically, high-ability students have an advantage relative to their low-ability peers with respect to the monetary as well as the non-monetary costs of studying abroad. First, they are more likely to obtain a scholarship based on their superior academic performance, and second, they are better able to organize a study stay abroad (c.f., Petzold and Moog 2018; Lörz et al. 2016). If these monetary and non-monetary obstacles are reduced by a massive change in the institutional environment, the relative cost advantage of high-ability students decreases and overall international student mobility increases, making a study stay abroad a less valuable labor market signal.

With the implementation of the European Higher Education Act ("Bologna-reforms"), the monetary as well as non-monetary costs of going abroad were reduced for all students. One explicit goal of the Bologna reforms was to foster international student mobility in an integrated higher education landscape. Specifically, the Bologna reforms stipulated the mutual recognition of academic credits and performances from foreign universities and the introduction of a comparable Bachelor-/Master-/PhD-system of academic degrees (EHEA 2020; European Commission 2021). As a consequence, especially the non-monetary costs of studying abroad decreased since (most of) the organizational barriers were removed. Additionally, the monetary cost obstacles declined with, e.g., financially supported exchange programs for students being established between universities in the participating countries.

With these changes in the institutional framework, the costs of study stays abroad declined for all students. As a result, a steep increase in the international mobility of German students in the last two decades (see Figure 1) can be observed. Today, more than one-third of all German students in later semesters have spent a part of their time at university abroad (BMBF and KMK 2018).

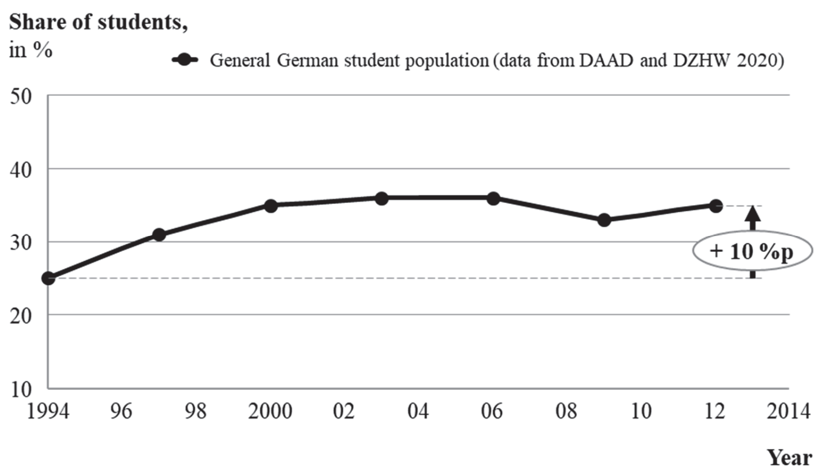

Figure 1. Development of German students in later semesters with study-related visits abroad (data from DAAD and DZHW (2020)).

Given these developments, we conclude that a 'simple' study stay abroad in the form of an exchange semester has become less exclusive and can, therefore, no longer be considered a credible signal of high-ability students to indicate their superior productivity. High-ability students wishing to distinguish themselves from low-ability students (following the paradigm of rational and utility-maximizing individuals) will, therefore, choose other signals of international qualification that low-ability students will not be able to produce at the same cost. As a consequence, we expect a change in the behavior of high-ability students towards signals where they still have a relative cost advantage over the general student population.

3. Methods and Data

3.1. Framework for the Analysis of International Student Mobility

We analyze the behavior of high-ability student mobility using the conceptual framework developed by Netz (2015). This framework distinguishes between (1) a pre-decision stage, (2) a planning stage, and (3) a post-realization stage. Between stages (1) and (2) is the decision threshold (*whether* to study abroad) and between (2) and (3) is the realization threshold (*where and how* to study abroad) (Netz 2015).

Our analyses are structured along this framework: First, we analyze the behavior of high-ability students at the decision threshold—whether they go abroad at all depending on the institutional framework while controlling for socio-demographics. The institutional framework is specified via the degree system: Diploma (Non-Bologna framework) vs. Bachelor/Master (Bologna framework). We estimate the impact of the Bologna system on the decision to go abroad (or not) using a Probit model. Potential interaction effects between the field of study and the change in the degree system are modelled via separate dummy variables. We then use post-estimation Wald-Tests to check for differences in the significance of the coefficients of the respective dummy variables. Second, we use Propensity score matching to isolate the effect of the degree system as follows: We match Bologna and Non-Bologna students based on their gender, age at study start, Abitur grade[3] cluster, field of study, and year of study start. Thus, we measure the average treatment effect of the change in the institutional framework (identified via the degree system) and the resulting lower costs to go abroad under the Bologna system. This allows us to isolate the effect of the change in the degree system from the influence of socio-demographic characteristics as well as other time-variant external factors.

In a further step, we look at the particular realization of the studies abroad for those students who went abroad, that is, for those who passed the decision threshold. Again, we use a Probit model plus Propensity score matching to analyze a possible change in behavior in the realization of studies abroad with respect to the number of stays per student, the cumulative duration of stays per student, the duration per stay, and the likelihood of completing one or more degrees abroad.[4]

Thus, we first looked *if* the students went abroad (decision threshold), then second at the particular realization of the sub-sample of students who went abroad in terms of the number of stays, duration, degrees, etc.

3.2. Dataset

Our dataset was extracted from the database hosted by a large German scholarship institution[5]. This database comprises anonymous CV information of the scholars over a period of 20 years since the organization's foundation. Scholarships are offered to pupils who ranked among the Top 3 in the respective Abitur (=high school diploma) cohort at their high school. Furthermore, unsolicited applications from students are possible. Key criteria for the selection of scholars are excellent academic performance, outstanding practical experience (e.g., via internships), and extracurricular engagement. Comparing the mean high school grade of the scholars in our sample with the general German student population[6] (Figure 2), it appears that the students in our dataset are indeed performing much better than their peers and are constantly better than the top 20% of the overall German student population. Hence, we refer to the students in our dataset as "high-ability" students.

From the original database, we extracted a dataset with detailed information on 10,844 German scholars with a study start between 1994 and 2013. We explicitly checked whether each student had completed his/her studies. We selected the three main fields of study in the database with 4764 students from Business & Economics, 2435 from Engineering, and 1897 from Natural Sciences & Mathematics. Hence, the final dataset used in our analyses included 9096 students.

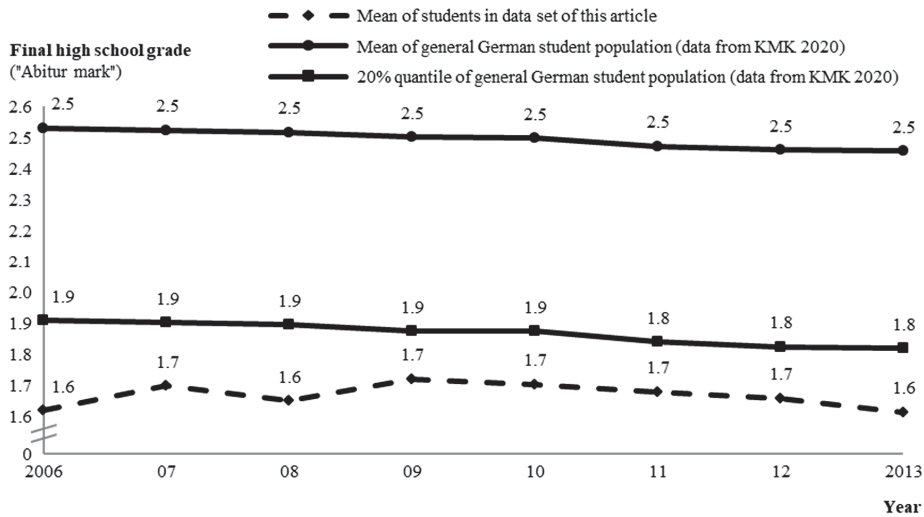

Figure 2. Comparison of mean final high school grades (data for general German student population from (KMK 2020)).

3.3. Differentiation of Bologna and Non-Bologna Students and Destinations

Germany signed the Bologna declaration in 1999 with the aim to implement the respective initiatives, e.g., the Bachelor/Master degree system until 2010 (BFUG 2020). Thus, our dataset includes both pre- and post-Bologna students, i.e., students studying under the Diploma and the Bachelor/Master degree system.

Both students and study abroad destinations were differentiated accordingly: Students were categorized based on the degree they obtained into Bologna (Bachelor/Master degree system) vs. Non-Bologna students (Diploma-system). In this sense, Bologna students represent the treatment group and Non-Bologna students the control group for our statistical analyses.

Bologna destinations are defined as higher education institutions in one of the 48 member countries of the European Higher Education Area (this is, countries participating in the Bologna reforms) according to BFUG (2020), except for universities in Germany as the home country of the students in our dataset. Higher education institutions in other countries are defined as Non-Bologna destinations.

Table 1 presents an overview of the key variables and descriptive statistics of the dataset. In some of the more detailed analyses, we further distinguish by field of study (Business & Economics vs. Engineering vs. Natural Sciences & Mathematics) and destination of study abroad, i.e., Bologna vs. Non-Bologna destinations.

Table 1. Overview of main variables and descriptive statistics.

Category	Variable	Description	Overall		Bologna Students		Non-Bologna Students	
			Mean	SD	Mean	SD	Mean	SD
Socio-demographics and secondary education characteristics	Gender	Dummy; 0 = male, 1 = female	0.31		0.35		0.27	
	Age at study begin	Age in years	20.18	1.20	19.99	1.19	20.33	1.18
	Final grade at high school (Abitur-mark)	Continuous, from 1.0 (best) to 4.0 (worst)[7]	1.60	0.48	1.67	0.51	1.55	0.45

Table 1. *Cont.*

Category	Variable	Description	Overall		Bologna Students		Non-Bologna Students	
			Mean	SD	Mean	SD	Mean	SD
Abroad study sections	Stay abroad	Dummy; 0 = no, 1 = yes	0.66		0.66		0.66	
	Number of stays abroad	Number of distinct stays abroad	1.01	0.99	1.06	1.03	0.96	0.94
	Aggregate duration of stays abroad	Length in months	11.23	18.34	12.31	20.19	10.32	16.58
	Average duration per stay abroad	Length in months per stay	10.24	9.03	10.34	9.48	10.17	8.65
	Share of study abroad time in percent of total study duration	Abroad study duration divided by total study duration[8]	0.15	0.22	0.17	0.26	0.12	0.18
	Number of degrees abroad	Number of distinct stays abroad with a duration of ≥12 months per stay	0.25	0.57	0.30	0.62	0.21	0.51
	Number of observations		9096		4140		4956	

4. Findings

As already mentioned above, we analyze the mobility patterns of high-ability students using the framework developed by Netz (2015); that is, we look at the behavior at the decision and the realization thresholds. At the decision threshold, we find a development in the going abroad behavior that is in line with the trend in the general student population. In particular, we see an increase in the mobility of high-ability students of 12–15 percentage points as a result of the implementation of the Bologna reforms, similar to the overall student population, where an increase of 10 percentage points is to be observed (Figure 1).

However, when looking at the realization of the study stay abroad, we observe a highly interesting, yet not surprising, change in behavior: We find a significant effect of the change in the degree system on the "degree mobility" of high-ability students.

4.1. Decision Threshold

Table 2 displays the results of two Probit models (D1 and D2) identifying the effect of the change in the institutional framework for going abroad following the Bologna reforms. We estimate the probability of going abroad during one's time at university depending on the degree system while controlling for socio-demographic characteristics as well as other education-related factors. In model D2, we additionally control possible interaction effects between the degree system and the field of study using six different dummy variables representing different combinations of the field of study and degree system.

Table 2. Statistical models D1 and D2 at decision threshold for stay abroad.

Variables		Model D1	Model D2
		Probit	Probit
Dependent variable		Stay abroad (yes/no)	Stay abroad (yes/no)
Independent variables		dy/dx	dy/dx
Gender	(Male)		
	Female	−0.02 (0.01)	−0.02 (0.01)
Age at study begin		−0.02 (0.00) **	−0.02 (0.00) **
Year of study start		−0.01 (0.00) **	−0.01 (0.00) **

Table 2. *Cont.*

Variables		**Model D1**	**Model D2**
		Probit	**Probit**
Final high school grade	(1. cluster) [1.0; 1.19]		
	2. cluster [1.2; 1.39]	−0.03 (0.02)	−0.03 (0.02)
	3. cluster [1.4; 1.69]	−0.04 (0.02) *	−0.04 (0.02) *
	4. cluster [1.7; 4.0]	−0.05 (0.01) **	−0.05 (0.14) **
Field of study	(Business & Economics)		
	Engineering	−0.21 (0.01) **	
	Natural Sciences & Math	−0.25 (0.01) **	
Degree system	(Diploma)		
	Bologna	0.04 (0.01) *	
Field of study × Degree system	(Business & Economics × Non-Bologna)		
	Business & Economics × Bologna		0.04 (0.02) *
	Engineering × Non-Bologna		−0.21 (0.02) **
	Engineering × Bologna		−0.16 (0.02) **
	Natural Sciences & Math × Non-Bologna		−0.24 (0.02) **
	Natural Sciences & Math × Bologna		−0.21 (0.02) **
Number of observations		9096	9096
Adj. R^2/Pseudo R^2		0.05	0.05

Legend: * denotes significance at 1%, ** at 0.1%; robust standard errors in parentheses.

Overall, we find intuitively plausible effects of both the socio-demographic characteristics and the education-related factors. In model D1, we find a statistically significant effect for the field of study. Compared to Business & Economics students, Engineering and Natural Sciences & Mathematics majors are, other things equal, 21–25 percentage points less likely to go abroad during their course of study. Gender does not have a significant effect in either of the two models, suggesting that male and female students are equally likely to go abroad. The coefficients of the four final high school grade clusters are statistically significant only for clusters 3 and 4, suggesting that students with poorer high school grades are less likely to go abroad during their time at university.

According to model D1, the change in the degree system increased the individuals' probability of going abroad by about 4 percentage points. The coefficients of the interactions between the change in the degree system change and the different fields of study (model D2) suggest that the effect is of a similar magnitude for all majors. Post-estimation Wald-tests reveal that the effect of the change in the degree system is statistically significant only for Business & Economics and Engineering students ($p < 0.05$) but not for students majoring in Natural Sciences & Mathematics.

To further isolate the effect of the change in the degree system, we applied Propensity Score Matching in model D3, the results of which are displayed in Table 3. This model confirms our initial observation, revealing a large and statistically significant effect. Under the Bologna system, high-ability students are 15 percentage points more likely to spend some time at a foreign university.

Summarizing, these models suggest an increase in overall international mobility for high-ability students studying under the Bologna system of 4–15 percentage points (depending on the model specification). This figure is of the same magnitude as in the general student population (+10 percentage points between 1994 and 2012; see Figure 1 above).

However, more detailed analyses show that this is true for Business & Economics and Engineering students only, while it does not hold true for Natural Sciences & Mathematics majors. In this latter group of high-ability students, no change in behavior occurred due to the implementation of the Bologna reforms. We discuss this finding in more detail below.

To analyze other changes in behavior, a more detailed view needs to be taken at the specific realization of studying abroad. Therefore, we now proceed to analyze the behavior at the realization threshold.

Table 3. Statistical model D3 at decision-threshold for stay abroad.

Variables		Model D3
		Propensity Score Matching
Dependent variable		Stay abroad (yes/no)
Average treatment effect (ATE)	Degree system Bologna	0.15 (0.04) *
Matching variables	Gender, Age at study begin, Final high school grade cluster, Field of study, Year of study start	
Number of observations		9096
Number of matchings [min; max]		1; 48

Legend: * denotes significance at 0.1%; robust standard errors in parentheses.

4.2. Realization Threshold

4.2.1. Overview

As outlined above, different characteristics of the stay abroad were used to identify changes in the behavior of high-ability students at the realization threshold. Our key finding here is a significant increase in degree mobility (Table 4; for further analyses, see Appendix A). We find a strong and statistically significant effect of the Bologna system on degree mobility, that is, the probability of completing a stay abroad of at least 12 months. Our other findings with respect to changes in the behavior of high-ability students when going abroad are in line with this finding: Under the new regime, the stays abroad are longer, and the number of stays has increased (the respective estimation results can be found in Appendix A).

Table 4. Statistical models R1 at realization threshold for stay abroad.

Variable		Model R1	
		Propensity Score Matching	
Dependent variable		Likelihood of completing a degree abroad in …	
		Bologna destinations	Non-Bologna destinations
Average treatment effect (ATE)	Degree system Bologna	0.23 (0.03) *	0.09 (0.04)
Matching variables	Gender, Age at study begin, Final high school grade cluster, Year of study start		
Sub-sample conditions		≥1 stay in Bologna destinations	≥1 stay in Non-Bologna destinations
Number of observations		3976	3095
Number of matchings [min;max]		1; 27	1; 16

Legend: * denotes significance at 0.1%; robust standard errors in parentheses.

Table 4 presents the results of our Propensity score matching model R1 showing the average treatment effect (ATE) of the change in the degree system (i.e., studying in the

Bologna regime) on degree mobility, i.e., the likelihood of completing a degree abroad by destination. We distinguish between Bologna and Non-Bologna destinations since the costs of going abroad, driven by the change in the institutional framework, are lower only in destinations participating in the Bologna reforms. Following the threshold logic developed by Netz (2015), we only consider students who have already passed the decision threshold and went abroad.

It appears from model R1 (Table 4) that degree mobility in Bologna destinations increased by 23 percentage points due to the change in the degree system. In contrast, no such change is to be found in Non-Bologna destinations.

4.2.2. Influence of Education Related Characteristics

In the next step, we again take a more nuanced perspective on the degree mobility of the students in our dataset. We now estimate two Probit models, including interaction effects between the change in the degree system and the field of study. Table 5 below displays the results.

Table 5. Statistical models R2 & R3 at realization-threshold for stay abroad.

Variables		Model R2	Model R3
		Probit	Probit
Dependent variable		Degree abroad (yes/no) in Bologna destination	Degree abroad (yes/no) in Non-Bologna destination
Sub-sample condition		Students with ≥1 stay in Bologna destinations	Students with ≥1 stay in Non-Bologna destinations
Independent variables		dy/dx	dy/dx
Gender	(Male)		
	Female	−0.01 (0.02)	−0.04 (0.02) **
Age at study begin		−0.02 (0.01) ***	−0.01 (0.01) *
Year of study start		−0.00 (0.00)	−0.01 (0.00) ***
Final high school grade	(1. cluster) [1.0; 1.19]		
	2. cluster [1.2; 1.39]	−0.06 (0.03) **	−0.02 (0.02)
	3. cluster [1.4; 1.69]	−0.06 (0.02) **	−0.02 (0.02)
	4. cluster [1.7; 4.0]	−0.06 (0.02) **	−0.04 (0.02) *
Field of study × Degree system	(Business & Economics × Non-Bologna)		
	Business & Economics × Bologna	0.20 (0.03) ***	0.07 (0.02) **
	Engineering × Non-Bologna	−0.03 (0.02)	0.03 (0.02)
	Engineering × Bologna	−0.01 (0.03)	0.03 (0.03)
	Natural Sciences & Math × Non-Bologna	0.00 (0.03)	0.03 (0.02)
	Natural Sciences & Math × Bologna	0.15 (0.04) ***	0.07 (0.04) *
Number of observations		3976	3095
Adj. R^2/Pseudo R^2		0.03	0.02

Legend: * denotes significance at 5%, ** at 1%, *** at 0.1%; robust standard errors in parentheses.

Interestingly, the findings regarding the effect of the change in the degree system vary considerably between the different fields of study and the two destinations. Model

R2 suggests that the effect of the change in the degree system on degree mobility into Bologna destinations is statistically significant for Business & Economics (+20 percentage points) and for Natural Sciences & Mathematics students (+15 percentage points). For Engineering students, we do not find a significant effect. Post-estimation Wald-tests confirm the significance of the degree system effect in these two fields of study ($p < 0.001$). In model R3, we observe a similar pattern across the fields of study. With respect to the degree of mobility of Business & Economics students into Non-Bologna destinations, the model displays an effect of +7 percentage points (post-estimation via Wald-test confirms significance, $p < 0.01$), while for Natural Sciences & Mathematics students, the Probit model also suggests a positive effect. Here, however, post-estimation via Wald-test shows this effect to be insignificant.

In total, this more nuanced perspective reveals that a statistically significant increase in degree mobility induced by the Bologna reforms can be observed only among Business & Economics students and for Natural Sciences & Mathematics students (for the latter only for Bologna destination). This pattern suggests that high-ability Business & Economics students are more likely to invest in the production of credible signals since they are, by education, familiar with the underlying concept. Thus, compared to their fellow students from other fields, they are more likely to complete a degree abroad to distinguish themselves from other Business & Economics students and signal their superior productivity to the labor market. Producing such a signal is more relevant for Business & Economics students since especially the more able and talented ones are typically looking for jobs offered by globally active multinational corporations. The same applies to high-ability Natural Sciences & Mathematics students looking for career opportunities in research, where an international qualification is also a relevant signal. In contrast, German high-ability Engineering students find an attractive labor market in their home country. For them, investing in the costly production of the signal "international qualification" is not that relevant and may even be detrimental to their labor market prospects if potential employers prefer practical experience accumulated via extended internships in prestigious companies, e.g., the German engineering or automotive industry.

The effects of the final high school grade on the probability of completing a degree program abroad are as expected for both destinations. Students with poorer final high school grades are less likely to complete a degree abroad. However, for Non-Bologna destinations, this effect is statistically significant only for the worst cluster of students. With respect to the Bologna destinations, all the coefficients fail to reach conventional levels of statistical significance.

4.2.3. Influence of Socio-Demographic Factors

Models R2 and R3 (see Table 5) show that gender seems to play a minor role only for degree mobility into Non-Bologna destinations. The female high-ability students in our dataset are 4 percentage points less likely to complete a degree in Non-Bologna destinations. For Bologna destinations, we fail to find a statistically significant gender effect, suggesting that male and female students are equally likely to complete a full degree program abroad.

Finally, the effect of the students' age at study start is statistically significant and plausible. With each additional year of age, the probability of completing a degree abroad decreases by 1–2 percentage points. Thus, older students are less likely to complete a degree abroad.

5. Discussion

5.1. Discussion of Theoretical Context

Our results clearly suggest that high-ability students use a degree abroad as the new labor market signal for an "international qualification" to distinguish themselves from low-ability students, for whom the respective monetary as well as non-monetary costs are higher. We suggest two main drivers for this development:

First, the costs of studying abroad have recently declined for all students due to changes in the institutional framework (i.e., the implementation of the Bologna reforms). As a result, the relative cost advantage of high-ability students compared to their fellow low-ability students decreased since international student mobility has increased considerably, and an exchange semester or study stay abroad has lost its exclusiveness (Teichler 2012). Thus, a "simple" study stay abroad, e.g., in the form of an exchange semester, is no longer a credible labor market signal.

Second, the changes in the institutional framework have opened up new opportunities for high-ability students to produce other signals where they still benefit from a relative cost advantage. Specifically, with the change towards the BSc/MSc/PhD degree system, an international degree is now fully recognized in the high-ability students' home country (here, Germany). More importantly, completing a degree abroad in a foreign language is arguably less costly for high-ability than for low-ability students for a number of reasons. First, high-ability students are more likely to access a full degree program abroad. Second, high-ability students are arguably better able to adapt quickly to new circumstances and to deal with language- and study-related challenges. Third, due to their performance, they are more likely to receive scholarships to fund their stay abroad, which is arguably more expensive than doing only an exchange semester. Fourth, in order to successfully complete a full degree program abroad, students must comply with a pre-defined course program. This means they have little (if any) freedom to choose "easy" courses, which a student who, in contrast, "just" does an exchange semester is likely to do. This is where the relative cost advantage of high-ability students in completing a degree abroad materializes. Since they are not able to avoid courses that are considered "difficult" by most students, such as, e.g., (advanced) mathematics and/or econometrics in a business program, they can convincingly document their intellectual superiority as well as their academic stamina.

Admittedly, the human capital theory could also serve as an explanation for the identified increase in the degree of mobility of high-ability students. For example, opportunities to acquire a foreign language and/or intercultural skills are certainly drivers for the motivation to study abroad (Doyle et al. 2010). However, isolating the relative contributions of signaling vs. human capital theory to explain the wide range of education and labor market phenomena is typically rather difficult (Weiss 1995; Huntington-Klein 2021). In the present case, we consider signaling theory to explain the observable development of international student mobility better for a number of reasons. Completing a degree abroad will certainly lead to some increase in human capital and, thus, improve labor market prospects. This, in turn, could be an incentive for high-ability students to complete a degree abroad—independent of the overall increase in international student mobility. However, in our context, the *incremental* increase in an individual's human capital, i.e., his/her abilities and skills, resulting from international experience, is likely to differ considerably between high- and low-ability students. The former will benefit far more from the signaling effect of a degree abroad as a means to distinguish themselves from their fellow students than low-ability students will benefit from a "simple" semester abroad as this is no longer considered a credible signal of international qualification. Thus, for high-ability students, we estimate the relative contribution of signaling to the motivation to complete a degree abroad to be higher than the contribution of an increase in the respective individual's human capital.

5.2. Differentiation of Findings by Field of Study

Our findings show a statistically significant effect of a change in the degree system on international student mobility between 1994 and 2013 of 15–23 percentage points, depending on the subsample and the particular model specification. When distinguishing between different fields of study, we find this effect to be particularly strong for Business & Economics students while being significant for Natural Sciences & Mathematics students only for Bologna destinations. Among Engineering students, the reforms did not have any effect on international mobility, neither into Bologna nor Non-Bologna destinations. These results are interesting and as expected: On the one hand, Business & Economics students are well aware of the underlying concepts of signaling and screening in the labor market. Hence, they are more likely to "apply" signaling consciously to maximize the value of each study decision they have taken. Consequently, they fully understand that completing a degree abroad is far more valuable for their labor market prospects than "just" completing an exchange semester abroad.

On the other hand, signals of international qualification are more relevant for multinational companies (Petzold 2017). Assuming that high-ability Business & Economics students are attracted by the career prospects in multinational companies, signaling an international qualification is, in turn, particularly relevant for them (see also Toncar et al. 2006). The same applies to Natural Sciences & Mathematics students looking for a career in international research institutions. In contrast, the potential employers of German Engineering students typically place a much lower value on an international qualification but look primarily at the individuals' performance in one of the arguably renowned German Engineering programs. Thus, high-ability German Engineering students find a highly attractive labor market in their home country and, therefore, do not need to invest in an international qualification.

5.3. Contextualization with Trends in Overall Student Mobility

To put this increase in the degree mobility of high-ability students into perspective, we compared this increase with respective data of the overall student population. To the best of our knowledge, no such increase can be found here: According to the European Tertiary Education Register (ETER), funded by the European Commission, the share of students completing a degree in another EU country has increased only marginally between 2011 and 2013 by 0.2 percentage points (European Commission 2020)[9]. Although these figures are not exactly comparable, the difference between the small increase in degree mobility in the general student population and the large increase among high-ability students in our dataset leads us to the following conclusion:

An exchange semester or a short-term study stay abroad has lost its credibility as a labor market signal as a result of an increase in overall international student mobility driven by the implementation of the Bologna reforms. Thus, high-ability students, particularly from Business & Economics and Natural Sciences & Mathematics, turned to completing a degree abroad as their new labor market signal demonstrating to potential employers their superior abilities and helping them to distinguish themselves from low-ability students.

Admittedly, our results would be even more convincing if we had access to comparable data from other countries, yielding similar results to the ones we have presented here. To the best of our knowledge, such data are currently not available. To partially compensate for this deficit, future research should focus on analyzing the mobility behavior of low-ability students and particularly their interest in completing a degree abroad. Moreover, future research should also analyze the returns to the labor market signal "international degree" by, e.g., looking at its impact on starting salaries and entry positions since these dimensions perfectly reflect how employers value the signal.

6. Conclusions

In summary, we confirm our initial hypothesis derived from signaling theory that utility-maximizing high-ability students will shift their attention from going abroad for one semester to alternative forms of international qualification as a credible labor market signal. Due to the increase in international student mobility induced by the Bologna reforms, the traditional signal of international qualification—a study abroad semester—has completely lost its exclusiveness as a labor market signal. We now find strong evidence that completing a degree program abroad is the new labor market signal for international qualification for high-ability students, particularly from the field of Business & Economics. Thus, in line with signaling theory, our data shows that with the implementation of the Bologna reforms, high-ability students complete academic degree programs abroad more often, while we fail to find any evidence for the same trend in the overall student population. Our interpretation that a degree program completed at a university abroad can be considered a credible labor market signal rests on the plausible assumption that while the Bologna reforms reduced the costs of studying abroad for all students, they did not affect the relative cost advantage of high-ability students to complete a full degree program abroad. In order to successfully complete a degree program abroad, the individuals' intellectual abilities and academic stamina are likely to play a far more important role than the institutional framework. The Bologna reforms have increased the probability of spending a semester abroad not only for high- but also for low-ability students, with the former changing their behavior even more than the latter. This, in turn, suggests that the non-monetary, e.g., mental costs of going abroad, continue to be more important than the monetary costs, which are now much lower than they used to be in the pre-Bologna era.

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Appendix A

Table A1. Further statistical models at realization threshold for stay abroad.

Variable		Model R4		Model R5		Model R6	
		Propensity Score Matching		**Propensity Score Matching**		**Propensity Score Matching**	
Dependent variable		Stay abroad (yes/no) in ...		Number of stays in ...		Cumulative duration of stay in ...	
		Bologna destinations	Non-Bologna destinations	Bologna destinations	Non-Bologna destinations	Bologna destinations	Non-Bologna destinations
Average treatment effect (ATE)	Degree system Bologna	−0.05 (0.07)	0.14 (0.07) *	0.18 (0.08) *	0.15 (0.04) **	10.26 (2.04) **	3.58 (2.04)
Matching variables	Gender, Age at study start, Final high school grade cluster, Field of study, Year of study start						
Sub-sample condition		≥1 stay abroad	≥1 stay abroad	≥1 stay in Bologna destinations	≥1 stay in Non-Bologna destinations	≥1 stay in Bologna destinations	≥1 stay in Non-Bologna destinations
Number of observations		6029	6029	3976	3095	3976	3095
Number of matchings [min; max]		1; 34	1; 34	1; 27	1; 16	1; 27	1; 16

Legend: * denotes significance at 5%, ** at 0.1%; robust standard errors in parentheses.

Table A2. Further statistical models at realization threshold for stay abroad.

Variable		**Model R7**		**Model R8**	
		Propensity Score Matching		**Propensity Score Matching**	
Dependent variable		Share of stays abroad of a student's total study duration for abroad stays in . . .		Duration per stay abroad in . . .	
		Bologna destinations	Non-Bologna destinations	Bologna destinations	Non-Bologna destinations
Average treatment effect (ATE)	Degree system Bologna	0.10 (0.02) *	0.03 (0.02)	4.41 (0.96) *	1.43 (1.57)
Matching variables	Gender, Age at study start, Final high school grade cluster, Field of study, Year of study start				
Sub-sample condition		≥1 stay in Bologna destinations	≥1 stay in Non-Bologna destinations	≥1 stay in Bologna destinations	≥1 stay in Non-Bologna destinations
Number of observations		3976	3095	3976	3095
Number of matchings [min; max]		1; 27	1; 16	1; 27	1; 16

Legend: * denotes significance at 0.1%; robust standard errors in parentheses.

Notes

1. More countries joined the reforms later on.
2. In this article, we define "studies abroad" as one or more study stays abroad or the completion of a tertiary degree in a foreign country.
3. The Abitur is the final qualification in secondary education in Germany. The overall performance of a student in secondary education is expressed by his/her final Abitur grade.
4. We also checked whether high-ability students chose stays at top universities worldwide more often as an alternative signal. Therefore, we calculated the share of students who completed a stay abroad at a top university defined as those ranked between 2010 and 2020 among the top 25 universities worldwide according to the Times Higher Education World ranking (Times Higher Education 2020). However, the share of students in our data set attending one of the top universities remains constant over time.
5. The data are proprietary and cannot be made available to other researchers.
6. Official statistics of the Conference of German Cultural Ministers (KMK) are only available back to 2006.
7. For subsequent analyses categorized into clusters within the data set ([1.0; 1.19], [1.2; 1.39], [1.4; 1.69]. [1.7; 4]).
8. Total study duration = total time at university (abroad + in home country).
9. Degree mobility figures for the overall European student population were calculated based on ETER data (Available online: European Commission 2020) on resident and mobile students at ISCED levels 6 & 7 (this is, Bachelor- & Master-level) and according to the formula employed by Sánchez Barrioluengo and Flisi (2017, p. 12): *Share of degree mobile students = ((number of mobile students)/(number of mobile students + number of resident students))*.

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Online Channel Sales Premia in Times of COVID-19: First Evidence from Germany

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Abstract: A presence on the web tends to be important for firms. Empirical studies show that firms with a better performance across various dimensions, and firms that are more internationally active, tend to have a website. Furthermore, a website helped firms to survive during the COVID-19 pandemic. An open question that is not discussed in the literature is how the use of online channels for sales is related to various dimensions of firm performance. This study contributes to the literature by using a unique recently released set of firm level data from Germany to investigate for the first time the links between online channels sales and firm characteristics. In a robustness check, the empirical investigation was replicated using strictly comparable firm level data from nine European countries, namely Austria, Belgium, Denmark, Finland, France, Ireland, Luxembourg, the Netherlands, and Sweden.

Keywords: online channels sales; firm performance; COVID-19; Germany 2021 Enterprise Survey Data Set

JEL Classification: D22; L25

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1. Motivation

A presence on the web is today considered as an important part of a firm's strategy to successfully make a living. This has tended to be even more important during the COVID-19 pandemic when quarantines and lockdowns have increased the costs of face-to-face contacts with (potential) buyers and sellers. Several recent empirical studies report findings that support this view:

Wagner (2022a) showed that in 2019, firms from 18 European countries that had a website were larger, older, more productive, and more often exporters, product innovators, process innovators, and (partly) foreign-owned firms compared to firms without a website. Good firms tend to have a website.

Wagner (2022b) used firm-level data from the Flash Eurobarometer 421 survey conducted in June 2015 in 34 European countries to investigate the link between having a website and international firm activities in small and medium sized enterprises (SMEs). He reports that firms that are present on the web more often export, import, and engage in research and development cooperation with international partners, work as subcontractors for firms from other countries, use firms in other countries as subcontractors, and perform foreign direct investments—both inside and outside the European Union. The estimated website premia are statistically highly significant after controlling for firm size, country, and sector of economic activity. Furthermore, the size of these premia can be considered to be large. Internationally active firms tend to have a website.

Using firm-level data from the World Bank Enterprise surveys conducted in 2019 and from the COVID-19 follow-up surveys conducted in 2020 in ten European countries, Wagner (2021) investigated the link between having a website before the pandemic and firm survival until 2020. The estimated positive effect of web presence was statistically highly significant ceteris paribus after controlling for various firm characteristics that are known to be related to firm survival. Furthermore, the size of this estimated effect can be considered to be large on average. Similarly, Muzi et al. (2022) report based on firm-level data collected for 34 economies up to 18 months into the COVID-19 crisis that businesses that have a website are more likely to continue existing. A web site helps firms to survive.

An open question that is not discussed in the literature on web presence and firm performance is how the use of online channels for sales is related to various dimensions of firm performance. Do better (larger, more innovative, more exporting) firms sell more using the web? Obviously, having a website does not mean that the owner uses it to sell goods and services—just think of yourself and your homepage on the web. This note contributes to the literature by using a unique recently released set of firm-level data from Germany to investigate for the first time the links between online channels sales and firm characteristics.

To anticipate the most important results, for Germany, we find that firms that use online channels more intensively for their sales tend to be larger, younger, more active in exports, and more innovative, while there is no link between labor productivity and intensity of use of online channels for sales.

In a robustness check that used strictly comparable data for nine other European countries and identically specified empirical models, however, these results could not be replicated. The picture holds for Germany only, and it differs from country to country. Any discussion of the reason for these cross-country differences is, however, far beyond the scope of this paper.

The rest of the paper is organized as follows. Section 2 describes the data used and gives the definition of the variables in the empirical investigation. Section 3 reports results from the econometric investigation of the size of online channel sales premia in the firms. Section 4 replicates the investigation for Germany with strictly comparable recently released firm-level data from nine European countries, namely Austria, Belgium, Denmark, Finland, France, Ireland, Luxembourg, the Netherlands, and Sweden. Section 5 concludes.

2. Data and Definition of Variables

The firm-level data used in this study are taken from the World Bank's "The Germany 2021 Enterprise Surveys Data Set". This survey was conducted between October 2020 and June 2022; data were released in July 2022.[1]

In the survey, firms were asked in question C22b, "At present time, does this establishment have its own website or social media page?" Firms that answered "yes" were classified as firm with a web presence; 91.3% of all German firms in the sample said that they did have a web presence—a much larger share than was reported for other countries in 2019 (see Wagner 2022a). This demonstrates that nearly all firms in Germany do have a website today, and that it does not make sense to look for any website premia here.

Furthermore, question EUD.1 asked for the percentage of the establishment's sales that was sold by using online channels (web-based platforms, social-media platforms, establishment's website, smartphone app): 72.5% of all firms in the sample reported zero online sales. This documents that by far not all of the 91.3% of firms with a website use it for online sales: a large fraction of firms with a website reported a share of online channels sales of zero percent. Table 1 documents in detail the reported percentage of the establishment's sales that was sold by using online channels.

Table 1. Share of establishment's sales made using online channels.

Percentage	Number of Firms
0	1.030 (72.54%)
1	19
2	13

Table 1. *Cont.*

Percentage	Number of Firms
3	9
4	5
5	47
6	1
7	1
8	4
9	1
10	68
12	2
13	1
14	2
15	14
17	1
19	2
20	30
24	1
25	15
30	24
34	2
35	4
40	11
45	5
47	1
50	28
55	4
60	15
52	1
70	13
75	3
80	11
84	1
85	2
90	5
93	1
95	2
96	1
98	1
100	19
	1.420

Source: The World Bank's "The Germany 2021 Enterprise Survey Data Set".

In the empirical investigation, the link between the percentage of sales of a firm using online channels and a number of firm characteristics was looked at. The selection of these characteristics was not based on a theoretical model—it was motivated by the results of empirical studies that looked at the difference in firm characteristics between firms with and without a website (summarized in the introductory section). The firm characteristics considered and the way they were measured here are listed below.

Firm size: Firm size was measured as the number of permanent, full-time individuals that worked in the establishment at the end of the last complete fiscal year at the time of the survey (see question I.1).

Firm age: Firm age was measured as follows. In question B.5 of the survey firms were asked, "In what year did this establishment begin operation?". Firm age is the difference between the year of the survey (reported in variable a15y) and the founding year.

Productivity: Productivity was measured as labor productivity, defined as the amount of total annual sales for all products and services (recorded in question d2) over the number of permanent, full-time individuals that worked in the establishment at the end of the last complete fiscal year at the time of the survey (see question I.1). Given that information on value added and on the capital stock used in a firm is missing in the data from the World Bank Enterprise Survey, more elaborate measures of productivity at the firm level, such as total factor productivity, cannot be used.

Exports: In the survey, the firms were asked for the percentage share of direct exports in total sales (see variable d3c). This variable was used as a measure for the export share in total sales.

Innovation: In the survey, firms were asked whether during the past three years this establishment had introduced new, improved products and services (see question H1). Firms that answered in the affirmative were considered as product innovators. Similarly, firms were asked whether during the past three years this establishment introduced any new or improved process, including methods of manufacturing products or offering services; logistics, delivery, or distribution methods for inputs, products or services; or supporting activities for processes (see question H5). Firms that answered in the affirmative were considered as process innovators.

Furthermore, firms were divided by broad sectors of activity (manufacturing, retail/wholesale, construction, hotel/restaurant, and services) based on their answer to the question for the establishment's main activity and product, measured by the largest proportion of annual sales (see question D1a1).

Descriptive statistics for all variables are reported for the whole sample used in the empirical investigation in Appendix A.

3. Testing for Online Channel Sales Premia in Firm Characteristics

To test for the link between firm characteristics listed in Section 2 and the intensity of the use of online channels for sales, an empirical approach was applied that modifies a standard approach used in hundreds of empirical investigations on the differences between exporters and non-exporters that has been introduced by Bernard and Jensen (1995, 1999). Studies of this type use data for firms to compute so-called exporter premia, defined as the ceteris paribus percentage difference of a firm characteristic—e.g., labor productivity—between exporters and non-exporters. These premia were computed from a regression of log labor productivity on the current export status dummy and a set of control variables:

$$\ln LP_i = a + ß\ Export_i + c\ Control_i + e_i \tag{1}$$

where i is the index of the firm, LP is labor productivity, Export is a dummy variable for current export status (1 if the firm exports, 0 else), Control is a vector of control variables, and e is an error term. The exporter premium, computed from the estimated coefficient ß as 100(exp(ß) − 1), shows the average percentage difference between exporters and non-exporters controlling for the characteristics included in the vector Control (see Wagner (2007) for a more complete exposition of this method).

Here, we look at differences between firms with various intensities of use of online channels in sales (instead of differences between exporters and non-exporters) and are interested in the existence and size of online channel sales premia (instead of exporter premia). Therefore, (1) becomes (2)

$$\ln LP_i = a + ß\ Onlinesales_i + c\ Control_i + e_i \quad (2)$$

where i is the index of the firm, LP is labor productivity, Onlinesales is the percentage share of sales of the firm sold using online channels, Control is a vector of control variables (that consists of dummy variables for sectors of economic activity), and e is an error term. The online channels sales premium ß shows the difference between firms with different intensities of using online channels for firm sales controlling for the broad economic sector the firm is active in.

Here, ß is computed by OLS for firm characteristics that are measured by continuous variables (firm size, firm age, labor productivity, export intensity). Firm size, firm age, and labor productivity are measured in logs, while export intensity is measured as the percentage of exports in total sales.

For firm characteristics that are measured by dummy variables (product innovator, process innovator) the empirical models are estimated by Probit instead. Therefore, (2) becomes (3)

$$Indicator_i = a + ß\ Onlinesales_i + c\ Control_i + e_i \quad (3)$$

and the online channels sales premia are computed as the estimated average marginal effects of the percentage of online channels sales shares.

Standard errors are robust standard errors adjusted for clusters in the six broad sectors of economic activity of the firms.

The results are reported in Table 2. For firm size, firm age, productivity, and export share, the reported premium is the estimated percentage increase that is associated with an increase in the share of online channel sales of a firm in its total sales by one percentage point (controlling for the broad sector of economic activity of the firm). For product innovator and process innovator, the premium is the estimated average marginal effect of an increase in the share of online channel sales by one percentage point on the probability that the firm is an innovator (controlling for the broad sector of economic activity of the firm).

Table 2. Estimated online channel sales premia for firm characteristics.

Firm Characteristic	Premium	t-Value
Firm size (number of employees)	0.37	2.12
Firm age (years)	−0.41	−3.44
Productivity (total sales per employee)	0.032	0.29
Export share (percentage)	0.057	2.56
Product innovator (dummy; 1 = yes)	0.0010	1.63
Process innovator (dummy; 1 = yes)	0.0012	3.46

Source: Own calculations with data from the World Bank's "The Germany 2021 Enterprise Survey Data set". The premium is the estimated percentage increase in firm characteristic for an increase in the share of online channel sales in total sales of the firm (controlling for broad sector of economic activity of the firm); t-values are based on robust standard errors, adjusted for clusters in sectors. For details see text.

We find that firms that use online channels more intensively for their sales tend to be larger, younger, more active in exports, and more innovative, while there is no link between labor productivity and intensity of use of online channels for sales. While some of these links can be considered to be quite strong—a 1% increase in the share of online channels sales in total sales is associated with an estimated increase in firm size by 0.37%, a decrease in firm age by 0.41%, and an increase in the export share by 0.057%—this is not the case for innovation activities. When averaged across firms, an increase in the share of online channel sales by one percentage point is associated with an estimated 0.001% increase in the probability of being a product innovator and a 0.0012% increase in the probability of being a process innovator.

4. Robustness Check: Strictly Comparable Evidence from Nine European Countries

Do the results reported for Germany here hold for other countries, too? To investigate this important question, all computations were replicated using strictly comparable firm-level data from the World Bank's Enterprise Surveys (that are available from the website mentioned in note 1) conducted recently in nine European countries, namely Austria, Belgium, Denmark, Finland, France, Ireland, Luxembourg, the Netherlands, and Sweden.

To start with, the share of firms with a web presence, which was 91.3% in the sample for Germany, was of comparable size in the other countries looked at here: it was 92.2% in Austria, 88.8% in Belgium, 97.4% in Denmark, 96.7% in Finland, 84.4% in France, 93.6% in Ireland, 89.54% in Luxembourg, 95.6% in the Netherlands, and 4.8% in Sweden.

Similarly, the percentage of firms that reported a zero percentage share of online channel sales (which was 72.5% in the sample of German firms) tended to be similar across the other countries looked at here: it was 71.7% in Austria, 74.1% in Belgium, 64.7% in Denmark, 68.3% in Finland, 76.6% in France, 75.0% in Ireland, 73.5% in Luxembourg, 65.6% in the Netherlands, and 67.1% in Sweden.

This indicates that today, on the one hand, nearly all firms in the ten European countries looked at here are present on the web, but that, on the other hand, a very large share of these firms (that varies from country to country between about two-thirds and three-fourths of all firms in the sample) does not generate any turnover from online channel sales.

How is the intensity of the use of online channels for sales linked to firm characteristics? The test for online channels sales premia in firm characteristics for German firms described in detail in Section 3 above revealed that firms that use online channels more intensively for their sales tend to be larger, younger, more active in exports, and more innovative, while there is no link between labor productivity and intensity of use of online channels for sales. Do these results hold for the other European countries looked at here, too? To investigate this important question, the empirical investigation for Germany was replicated with the strictly comparable firm-level data for the other nine countries. The results are reported, country by country, in Table 3.

For Austria, none of the estimated premia for a more intensive use of online channels for sales by the firms in the sample was statistically significantly different from zero at an error level of 5%. This is a totally different picture compared to the results we find for Germany. Note, however, that the positive and marginally significant link between a higher share of online channel sales in total sales and both a higher share of exports in total sales, and a higher probability of being a process innovator, is in line with the results for Germany. The same holds for the missing link between online channel sales and productivity.

For firms from Belgium, we find the results showed a statistically significant positive link between the share of online channel sales and three firm characteristics, namely firm size, product innovator, and process innovator; these results, and the missing link with productivity, are in line with the results found for Germany.

For firms from Denmark, productivity is negatively related to online channels sales, which is in stark contrast to the results for Germany. The link between online channel sales and the probability of product and process innovation, however, is positive in accordance with Germany.

Table 3. Estimated online channel sales premia for firm characteristics in nine countries.

Firm Characteristic	Premium	t-Value
AUSTRIA	(N = 566 firm)	
Firm size (number of employees)	−0.068	−0.38
Firm age (years)	−0.36	−0.82
Productivity (total sales per employee)	0.017	0.09
Export share (percentage)	0.199	1.70
Product innovator (dummy; 1 = yes)	0.00038	0.34
Process innovator (dummy; 1 = yes)	0.0016	1.75
BELGIUM	(N = 559 firms)	
Firm size (number of employees)	0.84	2.73
Firm age (years)	−0.047	−0.19
Productivity (total sales per employee)	−0.080	−0.15
Export share (percentage)	−0.021	−0.20
Product innovator (dummy; 1 = yes)	0.0037	2.56
Process innovator (dummy; 1 = yes)	0.0030	3.06
DENMARK	(N = 914 firms)	
Firm size (number of employees)	−0.19	−0.55
Firm age (years)	0.10	1.03
Productivity (total sales per employee)	−0.21	−2.17
Export share (percentage)	0.041	0.46
Product innovator (dummy; 1 = yes)	0.0023	1.77
Process innovator (dummy; 1 = yes)	0.0045	7.83
FINLAND	(N = 720 firms)	
Firm size (number of employees)	0.20	1.37
Firm age (years)	−0.0071	−0.05
Productivity (total sales per employee)	−0.16	−1.16
Export share (percentage)	−0.090	−4.58
Product innovator (dummy; 1 = yes)	0.00059	0.69
Process innovator (dummy; 1 = yes)	0.00093	1.58
FRANCE	(N = 1310 firms)	
Firm size (number of employees)	0.099	0.76
Firm age (years)	−0.24	−1.25
Productivity (total sales per employee)	−0.094	−1.05
Export share (percentage)	0.043	0.86
Product innovator (dummy; 1 = yes)	0.0019	4.45
Process innovator (dummy; 1 = yes)	0.00022	0.24
IRELAND	(N = 565 firms)	
Firm size (number of employees)	0.75	1.76
Firm age (years)	0.19	1.51
Productivity (total sales per employee)	−0.023	−0.04
Export share (percentage)	0.025	0.29
Product innovator (dummy; 1 = yes)	0.0024	1.05
Process innovator (dummy; 1 = yes)	0.0035	3.97

Table 3. *Cont.*

Firm Characteristic	Premium	t-Value
LUXEMBOURG	(N = 151 firms)	
Firm size (number of employees)	0.076	0.12
Firm age (years)	−0.24	−0.45
Productivity (total sales per employee)	−0.60	−1.76
Export share (percentage)	0.44	4.21
Product innovator (dummy; 1 = yes)	0.0030	0.85
Process innovator (dummy; 1 = yes)	0.0049	2.02
THE NETHERLANDS	(N = 773 firms)	
Firm size (number of employees)	0.60	2.19
Firm age (years)	0.067	0.53
Productivity (total sales per employee)	−0.11	−1.43
Export share (percentage)	0.023	0.41
Product innovator (dummy; 1 = yes)	0.0017	2.67
Process innovator (dummy; 1 = yes)	0.0023	2.85
SWEDEN	(N = 510 firms)	
Firm size (number of employees)	0.73	5.87
Firm age (years)	−0.12	−0.96
Productivity (total sales per employee)	0.24	2.04
Export share (percentage)	0.059	1.06
Product innovator (dummy; 1 = yes)	0.00083	0.90
Process innovator (dummy; 1 = yes)	0.0027	5.20

Source: Own calculations with data from the World Bank's Enterprise Surveys. The premium is the estimated percentage increase in firm characteristic for an increase in the share of online channel sales in total sales of the firm (controlling for broad sector of economic activity of the firm); t-values are based on robust standard errors, adjusted for clusters in sectors. See text for details.

For Finland, the only statistically significant result found here is the negative link between a higher share of online channel sales and a larger export share of the firm—a result that is contrary to the one reported for Germany.

For France, there is no statistically significant relationship between the firm characteristics looked at and the share of online channel sales in total sales of the firms, but a positive link between online sales and product innovation. The big picture, therefore, is different from the one reported for Germany.

The picture found for France is similar to the one reported for Ireland, where the only significant link is the one between a larger share of online channel sales and a higher probability of being a process innovator.

The small sample of firms from Luxembourg points to positive online channel sales premia for the share of exports in total sales and process innovations. Both findings are in line with the results for Germany.

In the Netherlands, firms with a larger share of online channel sales in total sales tend to be larger and more innovative. These results match the results reported for Germany, while the results for firm age and export share do not.

For firms from Sweden, we find a positive and statistically significant online channel sales premium with regard to firm size, productivity, and process innovation. While results for firm size and process innovation match the findings for Germany, the positive link with productivity is found for firms from Sweden only.

If we look at the results for the nine European countries not country by country but firm characteristic by firm characteristic, we learn that we do not find evidence for a clear picture. To state it differently, the estimated online channel sales premia are never statically significantly different from zero at a 5% error level for one firm characteristic across all countries looked at. Therefore, it does not make any sense to go one step further and try to compare the size of the estimated effects across countries.

Furthermore, the results reported for Germany are not matched by the results from a single other country. This illustrates again that it is important to replicate empirical results found in one data set for one country and one period of time with data from other samples (for other periods of time or other countries) using strictly comparable data and identically specified empirical models. Only results that stand this robustness test can be a sound basis for any further conclusions, and for evidence-based policy measures.

5. Concluding Remarks

This study reports for the first time estimated premia for important firm characteristics for a more intensive use of online channels for sales. For Germany, we find that firms that use online channels more intensively for their sales tend to be larger, younger, more active in exports, and more innovative, while there is no link between labor productivity and intensity of use of online channels for sales. While some of these links can be considered to be quite strong—a 1% increase in the share of online channel sales in total sales is associated with an estimated increase in firm size by 0.37%, a decrease in firm age by 0.41%, and an increase in the export share by 0.057%—this is not the case for innovation activities.

In a robustness check that used strictly comparable data from nine other European countries, namely Austria, Belgium, Denmark, Finland, France, Ireland, Luxembourg, the Netherlands, and Sweden, and identically specified empirical models, however, these results could not be replicated. The picture holds for Germany only, and it differs from country to country.

Any discussion of the reason for these cross-country differences is, however, far beyond the scope of this paper. Given that the estimated online channels sales premia are never statically significantly different from zero at a 5% error level for one firm characteristic across all countries looked at, it does not make any sense to go one step further and try to compare the size of the estimated effects across countries.

Furthermore, it is an open question (that is investigated at length in the literature where exporter premia are discussed) whether the premia reported for German firms are due to self-selection of firms into online channel sales or whether they are the effect of using online channel sales more intensively. For example, do larger firms use online channels more intensively (because they can deals more easily with the fixed costs associated with setting up and maintaining an online shop) or does the use of online channels for sales help firms to grow and become larger firms? Or are both of these possible directions of the observed positive link between firm size and the intensity of the use of online channel sales important? This issue cannot be investigated with the cross section data at hand. To answer this important question, longitudinal data for firms are needed that cover several years and that include a sufficiently large number of firms with various intensities of the use of online channels for sales over time. To the best of my knowledge such data are not available as of today. Let us collect it!

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

Appendix A

Table A1. Descriptive statistics for sample (N = 1420) used in estimations.

Variable	Mean	Std. Dev.
Firm size (number of employees)	73.84	485.41
Firm age (years)	36.40	34.46
Productivity (total sales per employee)	289,617.8	776,437.1
Export share (percentage)	11.93	22.02
Product innovator (dummy; 1 = yes)	53.24	
Process innovator (dummy; 1 = yes)	38.17	
Manufacturing (dummy; 1 = yes)	40.07	
Retail/wholesale (dummy; 1 = yes)	18.73	
Construction (dummy; 1 = yes)	12.46	
Hotel/restaurant (dummy; 1 = yes)	10.92	
Services (dummy; 1 = yes)	17.82	

Source: Own calculations with data from The World Bank's "The Germany 2021 Enterprise Survey Data Set"; for details see text.

Note

[1] The data and the questionnaire used are available free of charge after registration from the website https://www.enterprisesurveys.org/portal/login.aspx (accessed on 2 November 2022).

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Article

Is There a Union Wage Premium in Germany and Which Workers Benefit Most?

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Abstract: Using representative data from the German Socio-Economic Panel (SOEP), this paper finds a statistically significant union wage premium in Germany of almost three percent, which is not simply a collective bargaining premium. Given that the union membership fee is typically about one percent of workers' gross wages, this finding suggests that it pays off to be a union member. Our results show that the wage premium differs substantially between various occupations and educational groups, but not between men and women. We do not find that union wage premia are higher for those occupations and workers which constitute the core of union membership. Rather, unions seem to care about disadvantaged workers and pursue a wider social agenda.

Keywords: union wage premium; collective bargaining; union membership; Germany

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1. Introduction

In recent decades, unionization has been on the decline worldwide, and union density has reached a critically low level in many advanced countries (Visser 2019; Schnabel 2020). Increasingly often, unions' existence depends on their ability to attract and keep a loyal membership and to successfully represent their members' interests in collective bargaining. In addition to benefits such as worker representation and higher employment protection, unions typically promise to push through higher wages for their members. Union wage premia, meaning higher wages for union members compared with non-members with similar characteristics, are found in many, but not all, countries (for an overview, see Blanchflower and Bryson 2003). Depending on the institutional framework of the countries investigated, the empirical literature mainly uses two approaches for identifying such a premium (Bryson 2014): either estimating the ceteris paribus difference between the earnings of union members and non-members (i.e., a wage premium associated with union membership) or estimating the earnings difference between comparable workers covered or not covered by collective bargaining agreements negotiated by unions (a collective bargaining premium).

No matter which approach is used, the long-standing debate whether unions do have any effect at all on wages, that can be traced back to Adam Smith, seems to have been answered in the affirmative (e.g., Freeman and Medoff 1984; Bryson 2014; OECD 2019). However, it is an open question as to whether these union wage premia typically exist across the board or are specially targeted at the core groups of union membership. Put differently, are union wage premia higher in occupations that are highly unionized and are they higher for those groups of workers (like men and low-skilled workers) who are represented more than proportionally among union members?

This paper investigates this research question using a rich representative data set for Germany. Germany is an interesting case because it is often questioned whether the German institutional framework, where union wage settlements may spill over to non-union workers, can result in a union wage premium at all (Schmidt and Zimmermann 1991; Blanchflower and Bryson 2003). Our objectives are to investigate whether there is a union wage premium in Germany and whether it is higher for core groups of union membership. Thus, we first explain how a union wage differential can exist in Germany. Second, we add to the existing literature by estimating the union membership wage premium conditional on collective bargaining coverage. Using representative data from two waves of the German Socio-Economic Panel (SOEP), we show empirically that there is indeed a statistically significant union wage premium of almost three percent which is not simply a collective bargaining premium. Next, we demonstrate that this wage premium differs substantially between various occupations and educational groups, but not between men and women. Comparing the wage premia across occupations and for various groups of workers with the composition of union membership and the level of union density in these groups, we do not find that union wage premia are higher for those occupations and workers which constitute the core of union membership. There is some indication, however, that union membership particularly benefits some disadvantaged groups in the labour market (such as elementary workers or persons with no degree).

2. Wage Bargaining and the Union Wage Premium in Germany

In Germany, organizations of employers and employees have the right to regulate wages and working conditions without state interference.[1] Employers and unions negotiate collective agreements that are legally binding. These bargaining agreements may be set up either as multi-employer agreements at industry level or as single-employer agreements at plant level. Companies can decide to be covered by such an agreement, but they may also abstain from collective bargaining with unions and negotiate wages individually with their workforce.[2] If companies are bound by (industry- or plant-level) collective agreements, they cannot undercut, only improve upon the minimum terms and conditions laid down in these collective agreements, for instance by paying higher wages or providing longer holidays.

The wages and working conditions that were agreed in collective bargaining agreements apply only to the companies that are bound by the agreements (either directly or via membership in an employers' association) and to those of their workers who are members of the unions that signed the agreements. This means that non-union workers in a company are not entitled to be paid the union wage laid down in the collective agreement. However, it lies in the discretion of employers to extend the agreed wages to employees who are not members of the union. Such a practice may reduce these workers' incentive to join the union to receive the union wage. As many employers adopt such a strategy to keep unionization low, union wage gains regularly spill over to workers who are not union members. Against this background, it is often argued that due to the peculiarities of the institutional arrangements in Germany, a wage premium of individual union membership should not exist here (Schmidt and Zimmermann 1991; Blanchflower and Bryson 2003; Fitzenberger et al. 2013), although a premium from working in a company covered by collective bargaining may be possible.[3]

However, this argumentation overlooks several issues that may give rise to a genuine union wage premium even in Germany, i.e., a wage differential between union and non-union workers with similar characteristics in comparable workplaces that goes beyond the wage premium of being covered by collective bargaining. First, a union wage premium arises if companies determine to pay the wage laid down in a collective agreement exclusively to union members who are directly entitled to this wage, but do not extend this wage to non-union workers in the company. This increasingly seems to happen in Germany. A study by Fitzenberger et al. (2013) indicates that among those companies in Germany that are bound by collective agreements, the large majority does not pay all their workers according to the wage laid down in the collective agreement. A more recent investigation by Hirsch et al. (2022) finds that about nine percent of workers in plants with collective agreements do not enjoy individual coverage (and thus the union wage) anymore. Second, a union wage premium may arise if union members are more successful in individually negotiating higher wages than are non-members (or more often receive premiums above the contract wage in firms bound by collective agreements). The reason for these higher wages could be that union members, who are better informed than other workers, can draw on union support and enjoy effective legal protection by the union (Berger and Neugart 2012), are more assertive and in the end also more successful in wage negotiations. A third reason for a union wage differential could be that in firms not covered by collective bargaining, union members can credibly threaten to move to other, covered firms that pay union wages.[4] To prevent these workers from quitting, the firm may voluntarily pay them the union wage. They are now better paid than similar employees in this firm who are not union members.

In addition to these three mechanisms directly related to union membership that induce union wage premia, there are two other, indirect effects that may explain higher wages of union members. A fourth source of higher wages can be that union members have more stable employment biographies than non-union workers, for instance due to exit-reducing union "voice" (Freeman and Medoff 1984) and higher employment protection in firms with union representation (Goerke and Pannenberg 2011). Consequently, union members have higher tenure and accumulate more firm-specific human capital than other workers, resulting in higher wages (Bryson 2014). Finally, union members, who can draw on information and advice given by the union, may select themselves in larger firms and more profitable industries or occupations, thus obtaining higher wages than non-union workers (a similar relationship would be observed if workers in better-paying firms and occupations are more likely to become union members). Note that these indirect effects of unionism can be extracted from the raw union wage differential by including controls for tenure and labour market experience and dummies for firm size and occupation in the estimation.

Our estimation strategy for identifying a genuine union wage premium, which will be described in more detail below, uses regression analyses where the dependent variable is workers' log gross hourly wage. In the first step (or base model), the only regressor included is a dummy for union membership whose estimated coefficient reflects the raw wage differential between union and non-union workers. This raw differential is then adjusted by including many control variables into the regression such as educational, socio-demographic and labour market characteristics of workers, workplace characteristics and coverage by a collective bargaining agreement (full model), since union and non-union workers may differ in these characteristics that drive wages. The estimated coefficient of the union membership dummy now reflects the union wage premium, *ceteris paribus*. By including collective bargaining coverage among the regressors, we can also test whether the union wage premium is more than just a collective bargaining premium.

3. Data and Descriptive Evidence

We used the 2015 and 2019 waves of the German Socio-Economic Panel (SOEP).[5] The SOEP is a high-quality, representative dataset of more than 11,000 private households in Germany (see Goebel et al. (2019) for a description of the dataset) and is particularly suited for our analysis as it permits us to distinguish between the impact of collective bargaining coverage and individuals' union membership. Both waves used include information on union membership as well as on collective bargaining coverage. As we cannot differentiate between industry- and plant-level collective agreements in 2019, we created a dummy variable for collective bargaining coverage and used it in both waves (similar to Goerke and Huang 2022). Furthermore, the SOEP allows for the construction of hourly wages and enables us to control for a variety of individual- and firm-level characteristics such as education, age, family background characteristics, firm size and works council presence that potentially drive wage gaps between unionized and non-unionized employees.

Our dependent variable was the gross hourly wage (calculated using actual working hours) in 2015 prices. We focused the analysis on part- and full-time employees aged 16 to 65 and excluded self-employed individuals. Respondents working more than 30 h per week are defined as full-time employees. For the classification of occupations, we used the ISCO88 (1-digit) and drop armed forces and skilled agricultural and fishery workers as we observe only 129 individuals in this category (i.e., <1 percent). We classified sectors and industries based on NACE (level 1).

Using the 2015 and 2019 waves of the SOEP, Table 1 reports some descriptive statistics comparing union members and non-unionized workers. On average, union members receive hourly wages that are 18 log points higher than the wages of other employees. However, union and non-union workers also differ in many other personal and workplace characteristics that may affect wages. For instance, union members tend to be older and have higher job tenure as well as more labour market experience than other workers. They are more often educated to a lower level (having just basic secondary education, *Hauptschule*), more often have a permanent contract, and work in large firms. They are also more likely to be covered by a collective agreement and represented by a works council in the establishment. In contrast, union members are less often females, migrants, and part-timers. The occupational structure also differs between both groups, with union members being more often plant and machine operators and assemblers and less often service and sales workers than non-union employees.

Table 1. Descriptive Statistics by Union Membership.

	(1)	(2)	(3)	(4)	(5)
	Union Member		Not Union Member		
	Mean	Std.Dev.	Mean	Std.Dev.	Difference
Log Gross Hourly Wage (in EUR)	3.048	0.394	2.868	0.511	0.181 ***
Young 16–29 Years	0.079	0.271	0.109	0.311	−0.029 ***
Adult 30–39 Years	0.179	0.384	0.264	0.441	−0.085 ***
Adult 40–49 Years	0.281	0.450	0.329	0.470	−0.048 ***
Old 50–65 Years	0.480	0.500	0.327	0.469	0.153 ***
Basic Secondary Education (*Hauptschule*)	0.228	0.419	0.146	0.353	0.082 ***
Secondary Education (*Realschule*)	0.351	0.478	0.323	0.467	0.028 **
Upper Secondary Education (*Abitur*)	0.325	0.468	0.350	0.477	−0.025 **
Other Degree	0.070	0.256	0.145	0.353	−0.075 ***
No Degree	0.026	0.159	0.036	0.186	−0.010 ***
Female	0.396	0.489	0.532	0.499	−0.136 ***
East Germany	0.179	0.383	0.207	0.405	−0.028 ***
Migration Background	0.187	0.390	0.268	0.443	−0.081 ***
Married	0.650	0.477	0.617	0.486	0.033 ***
Labor Market Experience (in Years)	20.03	12.06	14.80	11.15	5.230 ***
Job Tenure (in Years)	16.82	12.05	10.07	9.662	6.750 ***
Part-time Contract	0.133	0.340	0.222	0.415	−0.089 ***
Permanent Contract	0.924	0.265	0.872	0.334	0.052 ***
Works Council	0.809	0.393	0.476	0.499	0.333 ***
Firm Size < 20	0.052	0.221	0.221	0.415	−0.169 ***
Firm Size 19 < X < 200	0.173	0.378	0.272	0.445	−0.099 ***
Firm Size 199 < X < 2000	0.254	0.435	0.226	0.418	0.028 ***
Firm Size > 1999	0.522	0.500	0.281	0.450	0.241 ***
Legislators, Senior Officials and Managers	0.026	0.158	0.041	0.199	−0.016 ***
Professionals	0.166	0.372	0.195	0.396	−0.029 ***
Technicians and Associate Professionals	0.288	0.453	0.278	0.448	0.010
Clerks	0.116	0.320	0.122	0.327	−0.006
Service Workers and Shop and Market Sales Workers	0.086	0.281	0.132	0.338	−0.046 ***
Craft and Related Trade Workers	0.135	0.342	0.093	0.290	0.042 ***
Plant, Machine Operators and Assemblers	0.114	0.317	0.056	0.231	0.058 ***
Elementary Occupations	0.069	0.254	0.084	0.277	−0.015 ***
Collective Bargaining Agreement	0.818	0.386	0.535	0.499	0.283 ***
Observations	2939		15,096		18,035

Notes: Dummy variables if not indicated differently. Reported differences are based on a regression of the selected variables on a union member dummy. Robust standard errors clustered at the individual level are used. ** and *** denote statistical significance at the 5%- and 1%-level, respectively. Data source: SOEP v36.

4. Estimating the Union Wage Premium

We defined our base model for individual i at time t as follows:

$$y_{it} = \alpha_0^{base} + \beta_1^{base} union_{it} + \epsilon_{it}^{base} \quad (1)$$

with $i = 1, \ldots, N$ and $t = 2015, 2019$ and where y_{it} is the log hourly wage, α_0^{base} represents the intercept, *union* is a dummy for union membership, β_1^{base} gives the corresponding raw union wage premium, and ϵ_{it}^{base} is an error term assumed to follow the standard assumptions.

For estimation of the adjusted or *ceteris paribus* wage premium, we estimated the following full model:

$$y_{it} = \alpha_0^{full} + \beta_1^{full} union_{it} + \gamma x_{it} + \epsilon_{it}^{full} \quad (2)$$

where β_1^{full} gives the union wage premium *ceteris paribus* and x_{it} represents a vector of regressors including dummies for highest educational attainment, marital status and migration background, age dummies, quadratic polynomials of labour market experience, job tenure as well as dummies for firm size, the type of contract, bargaining coverage, presence of a works council, occupation and survey year. Moreover, we added federal state fixed effects.

The results of our OLS estimations are presented in Table 2. In the base model that only includes a union membership dummy, being a union member is associated with hourly wages that are on average 19.8 percent (18.1 log points) higher than those of non-union members. This raw union wage differential is reduced to 2.6 percent when controlling for a large number of explanatory variables in the full model. By including controls for tenure and labour market experience and dummies for firm size and occupation in the estimation, we can account for the indirect effects of unionism discussed above.

Table 2. OLS Regression of Log Hourly Wages (Base and Full Model).

	(1) Raw Union Wage Premium Base Model	**(2) Adjusted Union Wage Premium Full Model**
VARIABLES	Log Hourly Wages	
Union Member	0.181 ***	0.026 ***
	(0.009)	(0.007)
Labor Market Experience (in Years)		0.013 ***
		(0.001)
Labor Market Experience Squared		−0.000 ***
		(0.000)
Job Tenure (in Years)		0.007 ***
		(0.000)
Basic Secondary Education (*Hauptschule*)		−0.047 ***
		(0.007)
Upper Secondary Education (*Abitur*)		0.110 ***
		(0.006)
Other Degree		−0.030 ***
		(0.009)
No Degree		−0.025 **
		(0.012)
Secondary Education (*Realschule*)		−0.009
		(0.005)
Young 16–29		−0.044 ***
		(0.008)
Adult 30–39		0.015 ***
		(0.005)
Old 50–65		0.005
		(0.006)
Adult 40–49		0.024 ***
		(0.005)
Legislators, Senior Officials and Managers		0.431 ***
		(0.015)
Professionals		0.344 ***
		(0.008)

Table 2. *Cont.*

	(1) Raw Union Wage Premium Base Model	(2) Adjusted Union Wage Premium Full Model
Clerks		−0.072 *** (0.008)
Service Workers and Shop and Market Sales Workers		−0.162 *** (0.008)
Craft and Related Trade Workers		−0.115 *** (0.008)
Plant and Machine Operators and Assemblers		−0.195 *** (0.009)
Elementary Occupations		−0.315 *** (0.009)
Technicians and Associate Professionals		0.084 *** (0.006)
Female		−0.100 *** (0.007)
Migration Background		−0.034 *** (0.009)
Married		0.039 *** (0.006)
Works Council		0.082 *** (0.007)
Firm Size <20		−0.191 *** (0.010)
Firm Size 19 < X < 200		−0.128 *** (0.008)
Firm Size 199 < X < 2000		−0.072 *** (0.007)
Part-time Contract		0.004 (0.009)
Permanent Contract		0.108 *** (0.011)
Collective Bargaining Agreement		0.012** (0.006)
Constant	2.868 *** (0.004)	2.584 *** (0.017)
Observations	18,035	18,035
R-squared	0.018	0.575

Notes: Survey years 2015 and 2019 used. Base model uses only the union member dummy as control (column (1)). Dummy variables used if not indicated differently. Full model (column (2)) also includes sector, survey year and federal state dummies. Deviation contrast transformation for categorical variables with more than two categories (i.e., for occupations, interactions of occupation with union membership, federal states, industries) applied. Robust standard errors clustered at the individual level in parentheses. ** and *** denote statistical significance at the 5%- and 1%-level, respectively. Data source: SOEP v36.

This approach shows that it is mainly workers' human capital (education), their occupational composition, their gender and contract status as well as firm size and the presence of a works council that affect wages. Interestingly, the existence of a collective bargaining agreement in the plant, though statistically significant, contributes little to wages and leaves us with a statistically significant *ceteris paribus* union-member wage differential. Put differently, there is a union wage premium of about 2.6 percent even when controlling for collective bargaining coverage (which is reflected in a bargaining premium of 1.2 percent).

As a robustness check, we ran the models in Table 2 separately for the two sample years 2015 and 2019. The results of these estimations did not change our insights. Although the union wage premium slightly decreased between 2015 and 2019, the estimated coefficients of the union member dummy remain positive and statistically significant, and they do not differ significantly between the two years. In order to address potential problems of unobserved heterogeneity of workers and plants, we also estimated a fixed effects model for the change in wages and union membership status between 2015 and 2019. This resulted in a union wage premium of 2.5 percent, which is very close to our cross-sectional estimate in

Table 2. Both robustness checks are not reported in tables but are available on request. This robust finding of a union wage premium that goes beyond a collective bargaining premium stands in contrast to most of the extant literature (such as Schmidt and Zimmermann 1991 or Blanchflower and Bryson 2003) which used to argue that there is no union wage premium in Germany.

As we mainly rely on a cross-sectional design (and our fixed effects model is restricted to only two years), our estimated union parameter should be interpreted cautiously and definitely not causally. It just shows that on average, union membership is associated with hourly wages that are almost three percent higher. Given that the union membership fee in Germany typically is about one percent of workers' gross wages (Goerke and Pannenberg 2011), it seems to pay off to be a union member, on average. However, this may not be true for all members alike, and therefore we will now investigate whether the union wage premium varies across occupations and between various groups of members.

5. Heterogeneities in the Union Wage Premium

In order to analyse potential heterogeneities in the union wage premium, we used the full model from Table 2 and add interaction terms of the union member dummy and various occupational, educational and socio-demographic characteristics. In particular, we looked at eight groups of occupations that can be identified in our data, at five educational categories and at gender—important characteristics where substantial differences exist between union members and non-members (as shown in Table 1).

Table 3 presents the results of an OLS estimation where interaction terms between the union member dummy and the occupation, education and gender dummies are added to the full model. The positive and negative interaction effects between union membership and occupation reported in column (1) indicate that the size of the union wage premium differs substantially across occupations. The same can be said for the interaction effects with education in column (2). In contrast, the interaction effect with gender is very small and not statistically significant (column 3).

Table 3. Regression of Log Gross Hourly Wages, Full Model with Interaction Terms.

	(1) Full Model with Interaction Terms (Between Union Member and Occupations	**(2) Full Model with Interaction Terms (Between Union Member and Education)**	**(3) Full Model with Interaction Terms (Between Union Member and Gender)**
VARIABLES		Log Hourly Wages	
Union Member	−0.022 *	0.042 ***	0.030 ***
	(0.012)	(0.011)	(0.009)
Legislators, Senior Officials and Managers	0.431 ***	0.413 ***	0.413 ***
	(0.016)	(0.015)	(0.015)
Professionals	0.345 ***	0.339 ***	0.339 ***
	(0.008)	(0.008)	(0.008)
Clerks	−0.066 ***	−0.071 ***	−0.070 ***
	(0.008)	(0.008)	(0.008)
Service Workers and Shop and Market Sales Workers	−0.155 ***	−0.156 ***	−0.156 ***
	(0.009)	(0.008)	(0.008)
Craft and Related Trade Workers	−0.119 ***	−0.115 ***	−0.115 ***
	(0.009)	(0.008)	(0.008)
Plant and Machine Operators and Assemblers	−0.214 ***	−0.190 ***	−0.189 ***
	(0.012)	(0.010)	(0.010)
Elementary Occupations	−0.312 ***	−0.299 ***	−0.300 ***
	(0.010)	(0.010)	(0.010)
Technicians and Associate Professionals	0.090 ***	0.079 ***	0.079 ***
	(0.006)	(0.006)	(0.006)
Union Member X Legislators, Senior Officials and Managers	−0.145 ***		

Table 3. *Cont.*

	(1) Full Model with Interaction Terms (Between Union Member and Occupations	(2) Full Model with Interaction Terms (Between Union Member and Education)	(3) Full Model with Interaction Terms (Between Union Member and Gender)
	(0.040)		
Union Member X Professionals	−0.029		
	(0.018)		
Union Member X Clerks	−0.009		
	(0.017)		
Union Member X Service Workers and Shop and Market Sales Workers	0.006		
	(0.017)		
Union Member X Craft and Related Trade Workers	0.033 **		
	(0.016)		
Union Member X Plant and Machine Operators and Assemblers	0.096 ***		
	(0.019)		
Union Member X Elementary Occupations	0.105 ***		
	(0.022)		
Union Member X Technicians and Associate Professionals	−0.056 ***		
	(0.013)		
Labor Market Experience (in Years)	0.014 ***	0.014 ***	0.014 ***
	(0.001)	(0.001)	(0.001)
Labor Market Experience Squared	−0.000 ***	−0.000 ***	−0.000 ***
	(0.000)	(0.000)	(0.000)
Job Tenure (in Years)	0.007 ***	0.007 ***	0.007 ***
	(0.000)	(0.000)	(0.000)
Basic Secondary Education (*Hauptschule*)	−0.051 ***	−0.049 ***	−0.048 ***
	(0.007)	(0.008)	(0.007)
Upper Secondary Education (*Abitur*)	0.113 ***	0.123 ***	0.113 ***
	(0.006)	(0.007)	(0.006)
Other Degree	−0.021 **	−0.024 **	−0.023 **
	(0.009)	(0.010)	(0.009)
No Degree	−0.031 **	−0.041 ***	−0.033 **
	(0.013)	(0.014)	(0.013)
Secondary Education (*Realschule*)	−0.011 *	−0.009	−0.010 *
	(0.006)	(0.006)	(0.006)
Young 16–29	−0.036 ***	−0.036 ***	−0.036 ***
	(0.008)	(0.008)	(0.008)
Adult 30–39	0.016 ***	0.017 ***	0.017 ***
	(0.005)	(0.005)	(0.005)
Old 50–65	−0.008	−0.009	−0.008
	(0.006)	(0.006)	(0.006)
Adult 40–49	0.028 ***	0.028 ***	0.028 ***
	(0.005)	(0.005)	(0.005)
Female	−0.102 ***	−0.100 ***	−0.100 ***
	(0.007)	(0.007)	(0.008)
Migration Background	−0.031 ***	−0.031 ***	−0.031 ***
	(0.009)	(0.009)	(0.009)
Married	0.040 ***	0.040 ***	0.040 ***
	(0.006)	(0.006)	(0.006)
Works Council	0.059 ***	0.060 ***	0.060 ***
	(0.007)	(0.007)	(0.007)
Firm Size <20	−0.186 ***	−0.186 ***	−0.186 ***
	(0.010)	(0.010)	(0.010)
Firm Size 19 < X < 200	−0.124 ***	−0.124 ***	−0.124 ***
	(0.008)	(0.008)	(0.008)
Firm Size 199 < X < 2000	−0.072 ***	−0.072 ***	−0.071 ***
	(0.007)	(0.007)	(0.007)
Part-time Contract	0.005	0.005	0.005
	(0.009)	(0.009)	(0.009)
Permanent Contract	0.098 ***	0.098 ***	0.098 ***
	(0.011)	(0.011)	(0.011)
Collective Bargaining Agreement	0.025 ***	0.025 ***	0.025 ***
	(0.006)	(0.006)	(0.006)

Table 3. *Cont.*

	(1) Full Model with Interaction Terms (Between Union Member and Occupations	(2) Full Model with Interaction Terms (Between Union Member and Education)	(3) Full Model with Interaction Terms (Between Union Member and Gender)
Union Member X Basic Secondary Education (*Hauptschule*)		−0.001	
		(0.014)	
Union Member X Upper Secondary Education (*Abitur*)		−0.067 ***	
		(0.014)	
Union Member X Other Degree		0.013	
		(0.021)	
Union Member X No Degree		0.065 **	
		(0.032)	
Union Member X Secondary Education (*Realschule*)		−0.011	
		(0.013)	
Union Member X Female			−0.005
			(0.013)
Constant	2.582 ***	2.535 ***	2.528 ***
	(0.022)	(0.021)	(0.018)
Observations	18,035	18,035	18,035
R-squared	0.592	0.590	0.590

Notes: Survey years 2015 and 2019 used. Regression also include sector, survey year and federal state dummies. Deviation contrast transformation for categorical variables with more than two categories (i.e., for occupations, educational categories, federal states, industries and interactions of occupation or educational categories with union membership) applied. Robust standard errors clustered at the individual level in parentheses. *, ** and *** denote statistical significance at the 10%-, 5%- and 1%-level, respectively. Data source: SOEP v36.

The resulting differences in the union wage premium across occupations, educational status and gender are visualized in Figures 1–3. The wage premia for the various groups are calculated by adding the corresponding estimated interaction effects and the union membership coefficient in each column. The grey bars in Figure 1 clearly show that the union wage premium varies substantially across occupations. It reaches almost nine percent among elementary occupations and in the group of plant and machine operators and assemblers. These two are occupational groups in which the average wage lies substantially below the average wage in the economy. The union wage premium is small and statistically insignificantly different from zero in several other occupational groups and it is even negative in some groups such as technicians and associate professionals and among legislators, senior officials, and managers.

Concerning educational categories, Figure 2 shows that the union wage premium is positive for workers with relatively little education, that is persons who either have no degree or only basic secondary education.[6] In contrast, the premium is not statistically significantly different from zero for workers with higher levels of education. The positive wage premium for low-educated workers corresponds to the positive effect for some low-wage occupations reported above. This suggests that union membership may be particularly beneficial for disadvantaged workers.

As mentioned above, the interaction effect with gender is statistically and economically insignificant. This means that the union wage premium does not differ between men and women (Figure 3).[7]

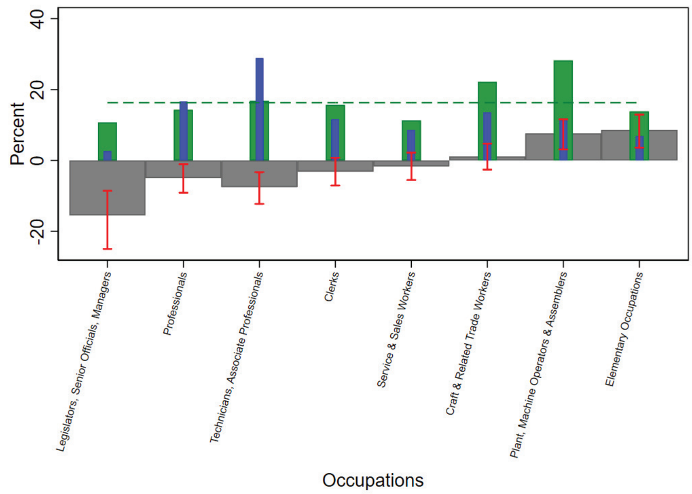

Figure 1. Union Wage Premia (Marginal Effects), Union Density and Union Membership Share by Occupation—Full Model with Interaction Terms between Occupations and Union Member Dummy. Notes: 18,035 observations in the survey waves 2015 and 2019. Grey shaded area represents the average union wage premium obtained from the interaction model in Table 3, column (1). 95% confidence intervals presented in red. Robust standard errors clustered at the individual level used. Blue bars represent the union membership share and green bars the union density within each occupation. Dashed line represents the union density in the full sample. Data source: SOEP v36.

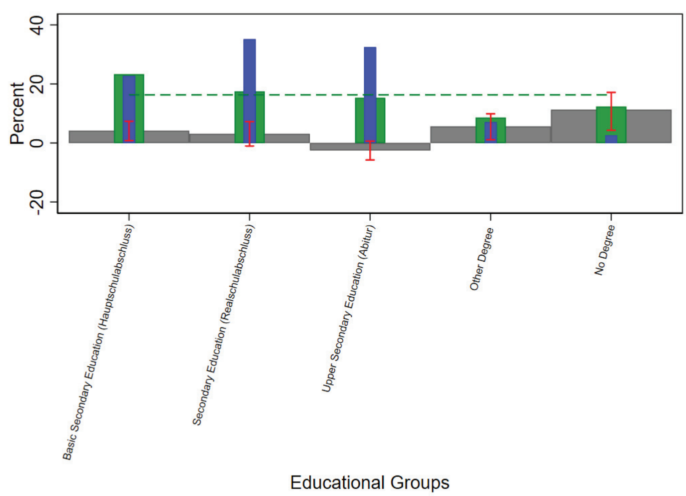

Figure 2. Union Wage Premia (Marginal Effects), Union Density and Union-Membership Share by Educational Group—Full Model with Interaction Terms between Educational Groups and Union Member Dummy. Notes: 18,035 observations in the survey waves 2015 and 2019. Grey shaded area represents the average union- wage premium obtained from the interaction model in Table 3, column (2). 95% confidence intervals presented in red. Robust standard errors clustered at the individual level used. Blue bars represent the union membership share and green bars the union density within each educational group. The dashed line represents the union density in the full sample. Data source: SOEP v36.

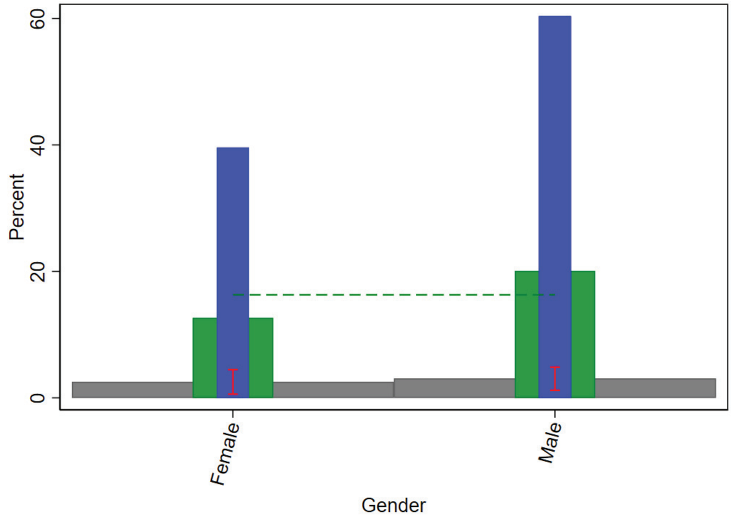

Figure 3. Union Wage Premia (Marginal Effects), Union Density and Union Membership Share by Gender—Full Model with Interaction Term Between Gender and Union Member Dummy. Notes: 18,035 observations in the survey waves 2015 and 2019. Grey shaded area represents the average union wage premium obtained from the interaction model in Table 3, column (3). 95% confidence intervals presented in red. Robust standard errors clustered at the individual level used. Blue bars represent the union-membership share and green bars the union density. Dashed line represents the union density in the full sample. Data source: SOEP v36.

6. Do Union Core Groups Benefit from the Wage Premium?

The substantial heterogeneity in the wage premium raises the question whether it is mainly core groups of union membership that benefit most, which would imply a strategic behaviour of unions that is straight to the point and successful. In order to address this question, we must identify which workers can be regarded as core groups. We can do this using two indicators, namely these groups' shares among union membership and their union density. Table 1 has shown that it is, in particular, men, low-educated workers, and workers in certain occupations (such as plant and machine operators and assemblers or craft and related trade workers) whose share is substantially higher among union members than among the rest of the workforce. A similar picture emerges if we look at union density, that is, the share of union members among the workforce or among certain groups of workers. Table 4 shows that in our sample, average union density is 16.3 percent, but it is clearly above average among men (20.1 percent), workers with basic secondary education (23.3 percent) and plant and machine operators and assemblers (28.2 percent) as well as craft and related trade workers (22.1 percent).

Looking at these two indicators, we find no clear relationship between the core groups and the size of the union wage premium. Starting with occupations, Figure 1 shows that union density is highest among plant and machine operators and assemblers, followed by the groups of craft and related trade workers and of technicians and associated professionals. The union wage premium is positive in the first group but statistically insignificant in the second and even negative in the third group. The group of technicians and associated professionals has the highest share among union members, but here the union wage premium is negative. In contrast, elementary occupations constitute only small groups among union members, but they record the highest union wage premium.

Table 4. Union Membership Shares, Densities and Wage Premia for Selected Groups of Workers.

Group	(1) Union Membership Share in %	(2) Union Density in %	(3) Adjusted Union Wage Premium in %
Basic Secondary Education (*Hauptschule*)	22.73	23.30	4.14
Secondary Education (*Realschule*)	35.15	17.50	3.13
Upper Secondary Education (*Abitur*)	32.46	15.30	−2.52
Other Degree	7.04	8.60	5.65
No Degree	2.59	12.30	11.30
Female	39.61	12.70	2.55
Male	60.39	20.10	3.08
Legislators, Senior Officials and Managers	2.55	10.70	−15.44
Professionals	16.60	14.20	−4.95
Technicians and Associate Professionals	28.82	16.80	−7.50
Clerks	11.60	15.60	−3.12
Service Workers and Shop and Market Sales Workers	8.61	11.30	−1.64
Craft and Related Trade Workers	13.54	22.10	1.10
Plant, Machine Operators and Assemblers	11.36	28.20	7.62
Elementary Occupations	6.91	13.80	8.62
Full Sample		16.30	2.63

Notes: 18,035 observations, survey years 2015 and 2019 used. Dummy variables if not indicated differently. Data source: SOEP v36.

A similarly diffused picture shows up concerning educational groups (see Figure 2). The union wage premium is small in the group with the highest union density (persons with basic secondary education) but it is largest in the group of workers with no degree, where union density is below average. Looking at membership shares, we see that the two largest groups of union members both have statistically insignificant wage premia whereas these premia are largest in the two smallest groups of union members (with no degree or other degrees).

Only concerning gender, there seems to be a certain connection (Figure 3). The core group of men, which has a higher union density and membership share than women, exhibits a higher union wage premium, but the difference to women is small and statistically insignificant.

7. Concluding Remarks

It is often questioned whether the institutional framework in Germany, where union wage agreements may spill over to non-union workers, can result in a specific union wage premium (other than a collective bargaining premium). Using representative data from the German Socio-Economic Panel (SOEP), this paper is the first which demonstrates empirically that there is indeed a statistically significant union wage premium of almost three percent which is not simply a collective bargaining premium. We further contribute to the literature by showing that this wage premium differs substantially between various occupations and educational groups, but not between men and women. Comparing the wage premia across occupations and for various groups of workers with the composition of union membership and the level of union density in these groups, we do not find that union wage premia are higher for those occupations and workers which constitute the core of union membership.

While our cross-sectional analysis does not allow us to make causal statements, the overall impression is that German unions do not appear to be particularly successful in delivering wage premia for their core groups of members (beyond the collective bargaining premium). Neither do we find higher union wage premia for women, which might be helpful in attracting more female members and thus reducing the substantial gender gap in German unions. Interestingly, however, being a union member seems to particularly benefit some low-wage groups in the labour market (such as elementary workers or persons with no degree). This finding may suggest that unions care about disadvantaged workers and pursue a wider social agenda. However, as long as these workers do not increasingly join unions (and there is no indication that they do so), creating specific union wage premia would not seem to be a promising strategy for stopping the decline in union membership.

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

Notes

1. For details on the German system of industrial relations and wage setting, see Gartner et al. (2013) or Keller and Kirsch (2021).
2. In 2019, 25 percent of establishments in Germany were covered by industry-level agreements and two percent of establishments by plant-level agreements. The remaining establishments relied on individual wage setting, although the majority of these establishments report to voluntarily use the wages set in (industry-level) collective agreements as a point of reference (see Kohaut 2020).
3. Although Wagner (1991) finds a positive wage effect of union membership for blue-collar (but not white-collar) workers, most individual-level studies report the absence of union wage effects in Germany (e.g., Schmidt and Zimmermann 1991; Blanchflower and Bryson 2003). Concerning the existence and size of a collective bargaining premium in Germany, the evidence is mixed (see, e.g., Gürtzgen 2009; Hirsch and Müller 2020; Kölling 2022). The recent analysis by Kölling (2022) estimates a wage premium of 2.5 percent for workers in establishments with collective bargaining agreements.
4. Although set in a different institutional environment, this argument bears some resemblance to the general idea by Rosen (1969) that the threat of unionization may raise wages in non-union firms.
5. Socio-Economic Panel (SOEP), data for years 1984–2019, SOEP-Core v36, EU Edition, 2021, doi:10.5684/soep.core.v36eu, https://www.diw.de/en/diw_01.c.814095.en/edition/soep-core_v36eu__data_1984-2019__eu_edition.html (accessed on 31 October 2022).
6. The same holds for workers with "other degrees" who often have foreign degrees that cannot easily be transformed into the educational classification used in Germany.
7. This finding is consistent with recent empirical evidence that unions do not dampen the gender pay gap in Germany (see Oberfichtner et al. 2020).

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economies

Article

Data Protection, Cookie Consent, and Prices

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Abstract: A legislative process is currently ongoing in the European Union to supplement the 2018 General Data Protection Regulation regarding ePrivacy regulation. The supplement is intended to complete the European data protection policy in significant areas. One addition would be for service providers on the Internet, who currently obtain the consent of their users via an opt-out provision, to always provide a paid alternative without disclosing data. This procedure is essentially aimed at overcoming "cookie consent fatigue", which can be observed in many cases. A simple economic exchange model shows that users, as data subjects, are basically faced with the choice of paying a monetary price for a service that will also preserve their privacy or using Internet services "for free" while negating data privacy preferences. The individual demand for data privacy coincides with the socially optimal demand only if there is effective competition in the markets for data and Internet services and if users are sufficiently informed. In an online laboratory experiment with students of the Leuphana University of Lueneburg, a between-subjects design was applied in which the control group only had the option to either "pay" for the use of the artificial intelligence DeepL via cookies by surrendering data or to abstain from the service altogether, with the two treatment groups additionally given the option to use DeepL in exchange for a monetary fee so that privacy was not violated. To be tested was whether the "monetary price for privacy" option better reflected users' privacy preferences than the current cookie opt-out solution. The results show that it was much less common for DeepL to be remunerated with the disclosure of data and less common for DeepL to be waived entirely.

Keywords: data protection; cookie consent fatigue; privacy concerns; legal remedies

JEL Classification: K12; K24; L86

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1. Introduction

Under the legislative process currently being pursued in the European Union for ePrivacy regulation, service providers on the Internet who wish to obtain their users' consent for the use of data by means of an opt-out rule must always have a paid alternative available. Users must be able to use the Internet provider's service without disclosing their personal data by choosing to pay a fee. This measure is intended to overcome "cookie consent fatigue" (Burgess 2018; Utz et al. 2019). Cookie consent fatigue occurs when users simply agree to the data privacy disclosure when asked for their consent, without reading the disclosure or thinking about what it means. We ask the question, "Does the planned regulation help ensure the desired individual level of privacy or data protection?"

From an economic point of view, data protection is focused on how personal data are collected, processed, and transferred. It is about protection of a person's private information and their right to be left alone (Acquisti et al. 2016). It is about protecting against intrusion into personality. In particular, it is about protecting individuals from the state interfering in their lives and restricting their ability to make decisions. When information about an individual becomes known, the state could use it to restrict the freedom of individuals (Solove 2006).

Acquisti (2010) and Larouche et al. (2016) see a variety of potential benefits for consumers when they disclose data: (a) recommendations for products and regional suppliers that have characteristics that fit well with consumer preferences; (b) consumers have to search less intensively for products and suppliers, which reduces their search costs; (c) personalized products are suggested, in extreme cases generated via the 3D printing process; (d) unwanted, non-matching advertising is avoided; (e) in social networks, communication with other participants in the network is made possible; (f) free content on the network is offered to the user; (g) ratings on the Internet can improve one's social status; and (h) users may be able to sell information about themselves. It can therefore be seen that the disclosure of data can very well be in the interest of an individual.

The disclosure of data can also lead to disadvantages for consumers: (a) information intermediaries may expose consumers to advertisements they do not desire to receive and that they would not otherwise receive without disclosing their data; (b) consumers are directed via targeted advertisements to products associated with excessive prices; (c) consumers may suffer harm when providers pressure them into consumer behavior that is disadvantageous; and (d) data may be used in an unpredictable way in the future, for example in the form of loss of reputation. If personal data is combined in an unpredictable way with other publicly available data, the negative effect may be compounded, for example: (a) personal data can be misused or stolen; (b) individuals may find themselves psychologically affected by the fact that information about them is in the hands of others; (c) information may be used to a person's detriment in the future when it is significantly more valuable; and (d) violations of privacy may result in material losses (e.g., higher prices), immaterial harms (e.g., anxiety), minor detriments (e.g., spam messages), or serious negative consequences (e.g., refusal of a mortgage in the case of identity theft or the denial of health insurance coverage). For more examples, see Acquisti (2010) and Larouche et al. (2016).

It is often feared that many individuals unintentionally disclose their data, although they claim in surveys that they do not want to disclose data—a "privacy paradox" (Barth and De Jong 2017). From the perspective of behavioral economics, the behaviors can be explained by (a) underestimating the long-term consequences of data pricing; (b) inappropriately preferring the current benefits of free use over the long-term disadvantages of loss of privacy; (c) that the way users respond to a data disclosure may mistakenly lead to wrong outcomes; or (d) inadvertently making wrong decisions. For example, selecting an opt-out box instead of opt-in box (Acquisti et al. 2015; Barth and De Jong 2017; Larouche et al. 2016; and basically rejecting Solove 2021).

The way the interests of data owners and data subjects interact in markets has been studied by economists for many years. Posner (1978, 1981) worried that privacy protection prevents the efficient exchange of information. For example, when unqualified applicants to a job are allowed to withhold characteristics relevant to the employer and are hired, the firm's productivity may be negatively impacted. At times, qualified applicants may not even be considered. Hiring unqualified applicants results in a firm's costs increase, and higher prices for consumers. Stigler (1980) takes this thesis even further by stating government interventions to protect poorly qualified applicants from revealing their data are at best ineffective and at worst harmful. They are ineffective because qualified applicants disclose information and unqualified ones "reveal" themselves as unqualified by withholding information. Harm occurs when the intervention is useless and generates costs. According to the work of Coase (1960), Laudon (1996), and Varian (2002), individual bargaining between both market parties discloses the efficient amount of information if the property rights to the data are clearly defined. Hermalin and Katz (2006) show that data disclosure can be associated with negative consequences. When it comes to insurance, data disclosure may result in being unable to insure oneself as a policyholder with a high loss potential, or being able to insure oneself only very expensively. To ensure ex ante insurability of all risks, policyholders may prefer a ban on disclosure.

In this paper, we restrict ourselves to looking at private consumers who might disclose data about themselves and producers who might use the collected data to produce Internet services. We ask whether the planned mandatory provision of Internet services, even with a fee, will lead to better consideration of privacy preferences. A simple economic exchange model shows that users, as data subjects, are faced with the choice of paying a monetary price for a service and preserving their privacy or putting privacy preferences second and using Internet services "free of charge". The individual demand for data privacy coincides with the socially optimal demand only if there is competition in the markets for data and Internet services, and users are sufficiently informed. To investigate this matter further, we conducted an online laboratory experiment with students from Leuphana University concerning the use of the artificial intelligence DeepL. The Control Group can either forgo the service DeepL by opting out via cookies or consume the service by agreeing to lower privacy via cookies. The two Treatment Groups had the additional option of choosing more privacy and paying a direct fee for DeepL; either they revealed a self-imposed willingness to pay greater than zero or they voted in a student ballot for a campus version of DeepL with an annual fee of EUR 10. The additional options for Treatment Groups to use DeepL with good privacy for a monetary price should better reflect the privacy preferences of users by accepting cookies with low privacy less frequently or doing without DeepL altogether. By specifying a concrete (market) price for the campus license (Treatment Group 2), privacy preferences should be taken into account even better than when stating willingness to pay (Treatment Group 1) because of observing a realistic price signal. Participants who expressed a sufficient willingness to pay for DeepL could use the paid version of DeepL currently available to the public for one year at a price of EUR 10; the difference from the higher actual price would have been reimbursed from university budget funds. In this respect, there was an ex ante incentive to seriously pursue participation in the experiment. The use of this between-subjects design is permissible because the three randomly selected groups differ little in their characteristics, views, and preferences.

Section 2 provides a brief overview of the current legal framework and describes the plans for ePrivacy regulation. Furthermore, the section summarizes available empirical evidence on the previous ePrivacy Directives and the General Data Protection Regulation, including reporting existing field experiments. Section 3 presents a market model of the individually and socially optimal demand for privacy. The experiment with Lueneburg students and its results are outlined in the Section 4. A summary and conclusion can be found in the Section 5.

2. General Data Protection Regulation and ePrivacy Regulation

The relatively new European General Data Protection Regulation (GDPR) can be seen as the current gold standard data privacy legislation (Buttarelli 2016). The regulation became applicable law in May of 2018 (De Hert and Papakonstantinou 2016). Building on the understanding that privacy is a fundamental human right in the EU (Article 8 European Convention of Human Rights; Article 7 European Charter of Fundamental Rights), the GDPR strengthens traditional privacy principles relating to the processing of personal data. For instance, it covers data processing lawfulness, purpose, and storage limitation, as well as data minimization (Article 5 GDPR).

Correspondingly, data processing is only lawful if prerequisites are fulfilled, such as obtaining the data subject's consent, the existence of a contract or another legal obligation, or if greater public interests prevail (Article 6 GDPR). The GDPR further provides data subjects with extensive and partially novel rights, such as the right to rectification, the right to erasure, the right to data portability, and the right to object (Articles 16, 17, 20, and 21 GDPR). Ultimately, rigorous liability and compensation payments, as well as administrative fines for unlawful conduct by data holders, reinforces the privacy rights of data subjects (Articles 82 and 83 GDPR). The standard case of consent sets legally significant hurdles (Buchner 2020, paras. 9–81). Consent depends on the prior agreement of the data subject, as subsequent consent is not sufficient. Consent must be conscious, voluntary, and informed. Voluntariness is in question if de facto coercion is exercised, if there is a clear power imbalance, or if an unreasonable "take it or leave it" decision exists. The data subject must be able to make an informed decision before giving consent (i.e., the required information must be sufficient, clear, and comprehensible to obtain informed consent). The consent must be sufficiently specific about the disclosure of the data concerned.

Along with the GDPR, additional data protection regulations apply, which are either anchored in the national Telemedia Act (TMG) or the Telecommunications Act (TKG), or European e-Privacy regulations, which are still based on directives from 2002 and 2009 and are set to be replaced shortly by the new ePrivacy regulation.

In the past, the European Union adopted two ePrivacy Directives. The first was in 2002, and the second in 2009. The latter included the obligation to obtain consent for cookies under an opt-in regime (González et al. 2020). As in the GDPR, the processing of personal data under sections 14 f of the TMG apply the principles of necessity and reservation of consent. According to Section 15 III of the TMG, cookies or comparable technologies that can record online usage profiles may be used if subscribers have consented on the basis of clear and comprehensive information, subject to the limits of civil law control of general terms and conditions, such as the inadmissibility of unreasonable disadvantage (Buchner 2020, paras. 161–174).

The new ePrivacy regulation, which will replace the previous two directives, is intended to provide greater protection for the rights of all users of electronic communications (SMS, e-mails, Facebook messages, social networks, etc.) (González et al. 2020; Council of the European Union 2021). Continuing in the spirit of the GDPR, gaining consent prior to the collection of data remains central. Specifically, the following shall apply:

- The regulation should apply to electronic communications of publicly available services and networks, including metadata (location, time, and data about recipients).
- The regulation protects European users, regardless of whether the service provider is located inside or outside the EU.
- The council proposes that explicit consent to cookies should only be valid if the user has the alternative option of paid use of the services and networks without cookie trackers.
- Users should be given the opportunity to set default settings for cookies—whitelists—via their browser settings, as well as to be able to easily change or revoke them. Whitelists of this kind are intended to counteract the problem that many users are overwhelmed by the large number of queries about cookie settings and therefore simply consent without recognizing the consequences of their consent.

According to the future ePrivacy regulation, consent should also be dispensable if there is no, or only very minor, threat of intrusion into privacy (Buchner 2020, para. 175).

The consequences of European data protection regulation were recently empirically investigated. From the analysis of almost 10,000 field studies on advertising campaigns from 2001 to 2008 in five European countries, Goldfarb and Tucker (2011) concluded 65 percent lower advertising effectiveness (less web bugs, cookies, and clickstream data) in online commerce. This trend is supposedly related to the e-Privacy Directives from the 2000s and its implementation in the member states.

There are a number of studies regarding the effects of the new GDPR, enacted EU-wide in May 2018. Goldberg et al. (2019) used data from the Adobe Analytics platform of 1508 companies to look at how the GDPR has affected salient metrics for European websites. Using a difference-in-differences approach, the new regulation appears to cause about a 10 percent decline in pages viewed, actual time of use, transactions made, and revenue generated. Johnson et al. (2020) extended the analysis by compiling a panel of over 27,000 websites, drawn from the 2000 most important Internet players from the EU, the USA, Canada, and worldwide. A special information technology tool was used to capture the relationship between internet players and web technology vendors, predominantly concerning advertising, web hosting, audience measurement, and social media. They looked at data from just before the GDPR came into force in May 2018, compared to the end of 2018 when the regulation was in full effect. In the short term, the market shares of the small web technology vendors fall in favor of the large ones such as Google or Facebook, which can be interpreted as causal due to the use of the difference-in-differences approach.

They attributed this short-term concentration movement to the fact that large vendors were more likely to be able to provide guarantees that they could meet the new data protection requirements. After a few months, the shift seemed to disappear. Building on the previous data set and using similar methodology, Goldberg et al. (2021) found that after the GDPR took effect, page views fell by an average of 11.7 percent. Recorded revenue also fell by 13.3 percent. Just under 10 percent of users refused consent, which explained the 9.4 percent effect on page views and 7.6 percent effect on revenue. The large remainder came at the expense of the GDPR in the form of more difficult marketing activities, whether among consenting or non-consenting users.

Lefrere et al. (2020) compared websites in the EU versus those from non-EU countries in terms of website content. According to their estimates, the introduction of GDPR in May 2018 did not seem to have a negative impact on the content of websites. Peukert et al. (2020) observed over 110,000 websites over 18 months before and after the GDPR introduction. On one hand, there were more informative privacy policies, but on the other hand, Google's market power increased. Jia et al. (2018) concluded from their data that in the short term following the tightening of data protection in Europe in 2018, investments in young, European tech companies declined compared to investments in the United States. Their follow-up paper (Jia et al. 2021) showed similar findings. Using a difference-in-differences approach, Aridor et al. (2020) used data from European and U.S. online travel agencies from the first eight months of 2018 to find the following effects from the newly introduced GDPR opt-out rule. Approximately one-eighth of users took the opt-out option, but the remaining users stayed longer on the website. Internet providers could therefore track users for a longer period of time, which they described as an eight percent higher trackability.

Utz et al. (2019) conducted field experiments on how the frequently observed cookie consent fatigue could be reduced by designing websites differently. For about 1000 consent variants on currently existing websites of a German e-commerce provider, more than 80,000 real website visitors were confronted with different forms of consent. Experiment 1 looked at whether the position of the consent notice on the screen influenced the decision (14,135 visitors). Experiment 2 asked whether the number of choices and the graphical highlighting of answers (nudging) had an impact (36,530 visitors). Experiment 3 tested whether the link to a privacy policy or the use of non-technical language, such as "this website collects your data", was relevant to 32,225 visitors. Approximately 100 participants took part in an online follow-up survey. According to the descriptive results, users were more likely to respond to a notice at the bottom left of the screen. They were more willing to accept cookies if they had the choice to accept or not accept them, instead of just agreeing to them, and they responded strongly to nudging.

Machuletz and Böhme (2019) investigated how 150 mostly first-year undergraduate computer science students at the universities of Muenster and Innsbruck responded to different consent dialogues and how they evaluated their decision afterwards. Without disclosing the goal of the study, participants were given the task of searching for a flight with departure and destination locations and dates. The search engine website had different, randomly assigned privacy notices that served as the lab experiment. Treatment Group 1 (the "deception variant") received a comprehensive text with three levels of data disclosure to choose from. If one chose the graphically highlighted button, all three levels were selected. Treatment Group 2 received only one level to choose from, but with the consent button highlighted. The Control Group could select the three options individually and the confirmation button was not highlighted. Users voted for more data collection purposes with highlighted buttons when there were multiple options to choose from, and much more so than in the work of Utz et al. (2019). The follow-up survey strongly suggested that participants were deceived in both treatments. The number of areas for which consent can be given had no significant effect.

3. Data Protection in Markets

Adapting from the textbook version of general equilibrium in Nechyba (2018), the following model shows how an individual, W, offers an Internet service based on data as well as providing the data itself, as well as how it acts in a profit-maximizing or utility-maximizing manner in competition. It is a matter of how much data the individual voluntarily discloses. In other words, how much privacy would the individual give up, and how much data would not be disclosed? The model shows it corresponds to the optimum level of data protection in society as a whole.

The individual W produces only one service, x She provides information in connection with the Internet and with the help of a search engine, or she sells a good or service by using the Internet. In either case, provision of information is always present. W thus becomes a data holder. Additionally, the individual W also provides data about herself, i.e., she gives away information about herself, the data subject. In extreme cases, she becomes a "glass human being" by providing too much information.

Figure 1 shows how the data owner W uses data d to provide service x. The production function $x = Ad^{\beta}$ with A as a constant and $0 < \beta < 1$ (production function is concave) applies to her. Consequently, W produces with positive but diminishing marginal returns if all other input factors such as labor and capital are constant.[1] In other words, more data from individuals help to provide x, but the increase in x decreases as data availability increases.

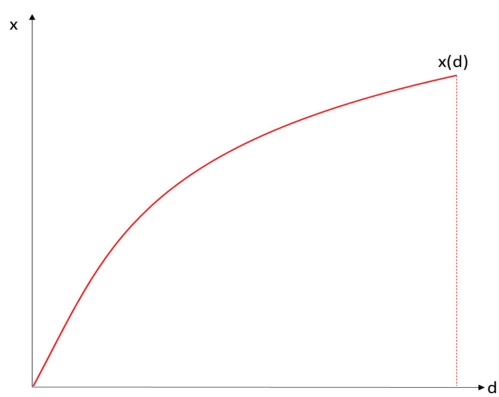

Figure 1. Production function of a data owner.

The data subject derives utility from the service x and disutility from the disclosure of its own data to third parties. In Figure 2, let the point S be given with the consumed amount of x_S and the disclosed amount of data d_S. Starting from d_S, a disclosure of further information in the amount of +d would mean a utility loss for the data subject, which would just be compensated by the increase in x by the amount of x`. S and S` lie on the same indifference curve I_1. Moving from S`` to S```, i.e., by definition the same amount of data disclosure +d, the individual "demands" a significantly larger amount of x to be compensated for the loss of privacy. In other words, the more individual data already disclosed, the more severe the resulting inconvenience. Only higher amounts of x can "compensate" for the loss of privacy. At the disclosure level D, at d = D, the data subject has disclosed all her data, and the level of privacy is zero. The data set D thus becomes the endowment point for the individual, which can be maximally disclosed. For example, the data subject's utility function can be written as $x^{\alpha}(D-d)^{(1-\alpha)}$ (Cobb–Douglas utility function with $0 < \alpha < 1$). In Figure 2, the point V compared to S' for a given price of data d means a higher availability of the service x, and consequently a higher indifference curve I_2 is obtained. Indifference curves that run to the upper left, such as I_3, are associated with even higher utility.

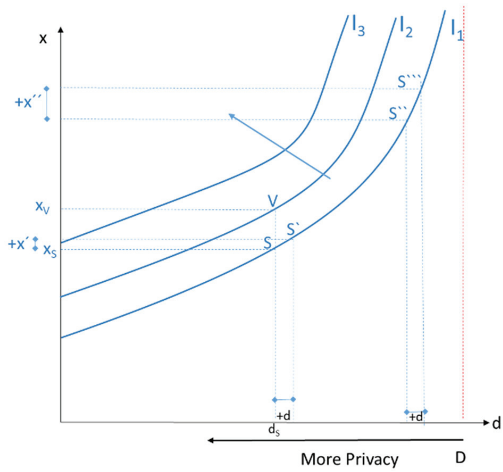

Figure 2. Indifference curves of a data subject.

Considering the data owner and data subject as one unit, the highest possible utility on the indifference curve I_3 would be reached at point C* for a given production function x(d) (Figure 3). Consequently, the data quantity d* would be revealed and not the maximum quantity D. Of the service x, x* is produced and consumed, but not up to x_D. In this respect, the non-consumed difference between x_D and x* can be interpreted as the "price" for preserving (partial) privacy, D-d*. The difference D-d* would thus be the optimal privacy for society as a whole if the same production and utility functions apply to all individuals; however, the data d* are disclosed in the optimum circumstance (see Appendix A).

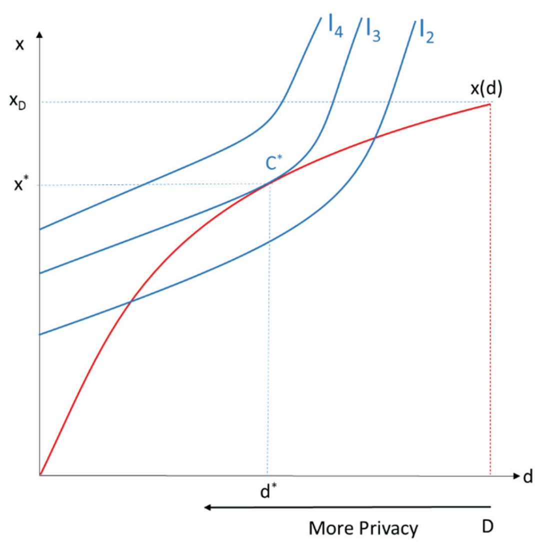

Figure 3. Welfare-optimal data protection.

If we return to separate individuals for data owners and data subjects, owners face the competitive goods price p for their provided goods. Data subjects can obtain the competitive factor price t for their data, and we can show that utility-maximizing or profit-maximizing individuals experience socially optimal privacy. Factor prices for data are either explicit prices (the data holder pays a price for data collected from the data subject) or are implicit (the data subjects forgo monetary compensation for loss of privacy in exchange for quantities of x for free). Prices for the use of Internet services correspond either to direct monetary amounts (a "cash price") or to the utility losses of limited privacy if no monetary payment is made.

All combinations of quantities of data d used, for which the constant factor price t has to be paid, and different levels of services produced, which are sold at the constant price p and lead to the same profit level π, represent isoprofit lines (Figure 4). Consequently, in general,

$$\pi = \mathrm{px} - \mathrm{td}$$

$$\mathrm{x} = \frac{\pi}{\mathrm{p}} + \frac{\mathrm{t}}{\mathrm{p}}\mathrm{d}.$$

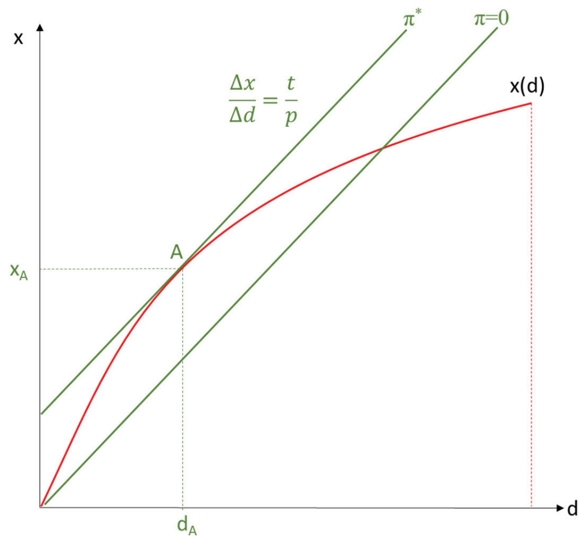

Figure 4. Data holder and optimal data demand.

The slope of the isoprofit line $\left(\frac{\Delta \mathrm{x}}{\Delta \mathrm{d}}\right)$ is thus equal to $\frac{\mathrm{t}}{\mathrm{p}}$. Constant prices imply competition in the service market for x and in the factor market for d. The isoprofit line through the origin corresponds to zero profit. Only goods along the production function x(d) can be produced at most. The data holder achieves highest possible profit in A, such that d_A is demanded as data disclosure and quantity x_A is supplied; the profit achieved is π*.

Given commodity and factor prices p and t or isoprofit line π', the data subject chooses the highest possible indifference curve I_4 with point B, and thus the utility-maximizing data disclosure d_B or the optimal level of privacy D-d_B (Figure 5). The utility-maximizing amount of consumption occurs at x_B.

If there were no effective data protection, data owners could obtain data for free (t = 0), and isoprofit lines run horizontally to the abscissa (Figure 6). The highest possible isoprofit line π** is reached at D where the data subject discloses too much of her data, more precisely, all her data (privacy D-d = 0), and consumes too many data-driven goods (x_D). The data subject then achieves a lower utility level ($I_1 < I_4$) than she would with an effective data protection policy in place.

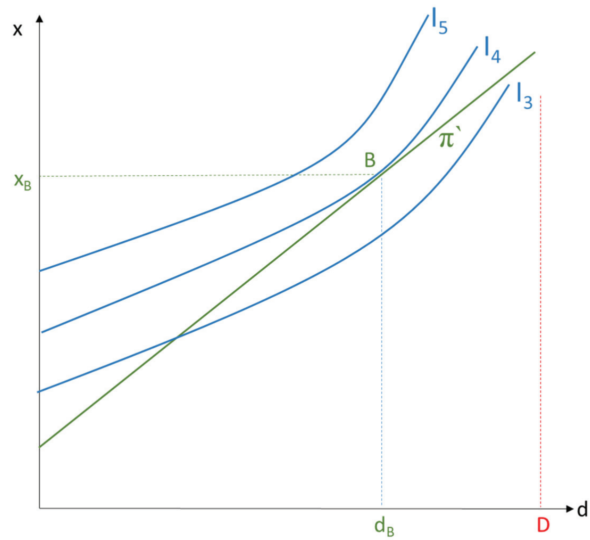

Figure 5. Data subject and optimal data supply.

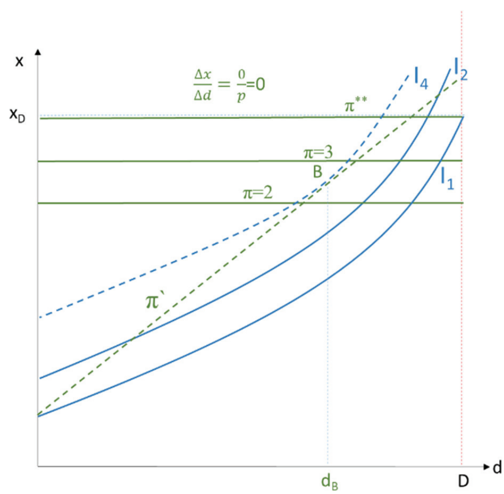

Figure 6. No effective data protection.

For equilibrium on the data market and thus for the realization of the optimal data protection level (D-d*) or the optimal amount of use of the data in B (d = d*), the data market must also be cleared. In Figure 7, more data would be offered than demanded, $d_B > d_A$. The data usage price t would have to decrease toward the equilibrium. At the same time, the usage price p would be too low because there would be excess demand for x ($x_B > x_A$). According to Equation (2), the slope of the isoprofit line t/p would have to fall until demand equals supply in both markets (t*/p*), which would be the case at point C** in Figure 8. As shown in Appendix A, Point C* in Figure 3 and Point C** in Figure 8 coincide. In the data market with utility-maximizing data subjects, the optimal level of privacy or data protection (D-d*) automatically results, and the data disclosed equals d**. At the same time, in the service market x, the optimal quantity x** is supplied and demanded.

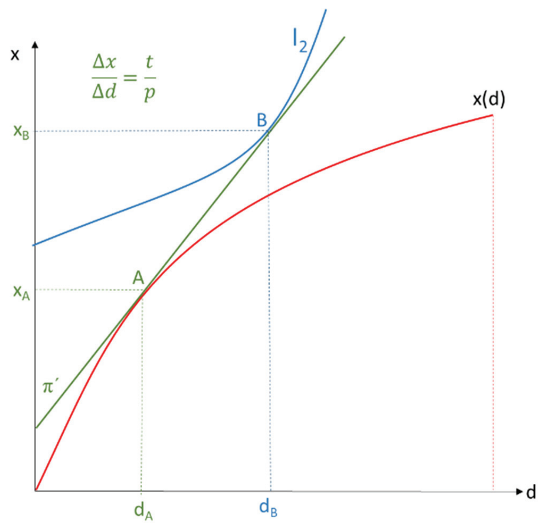

Figure 7. Disequilibrium in the data market.

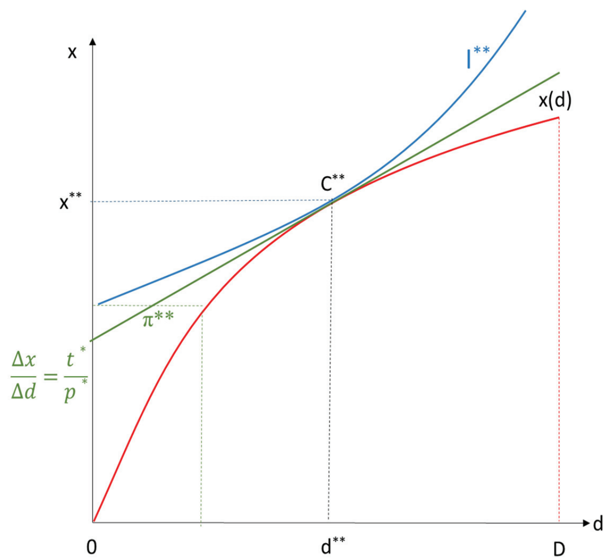

Figure 8. Equilibrium in the data market.

An obligation under the new ePrivacy Regulation to finance the provision of good x by a monetary price in addition to "financing from the disclosure of data" can be explained with the help of Figure 9. The starting point would be D, where all relevant data are disclosed (no data protection), but data-driven goods to the extent of x_D are consumed "free of charge" in return. If, however, the obligation to make a counteroffer with a monetary price p were to take effect, the utility-maximizing point C** would be reached under competition. At the market price for x in the amount of p*, the monetary amount (x_D-x**)p* would be paid for the smaller but optimal quantity x**; data would only be given up to d**, and the data quantity D-d** would not be disclosed. The new "exchange-money-payment" for x is better for the data subject because a higher indifference curve I** is achieved compared to I′. Admittedly, this increase in utility occurs only if the principles of voluntary exchange apply. Above all, data subjects must be properly informed and data owners must not have monopolistic influence in the data market.

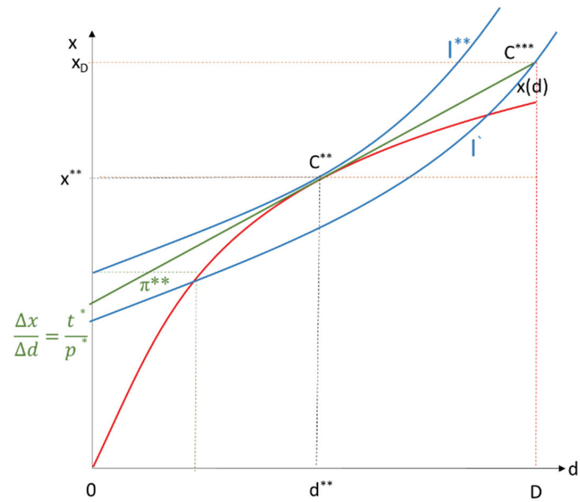

Figure 9. Monetary offer.

This simple welfare economic model of optimal privacy, in which the data owner and data subject appear as one person, shows that there is an optimal level of privacy. This optimal level can be achieved either by paying a monetary price for the Internet service or by giving up data. Admittedly, the conditions of voluntary exchange must be met for this to occur, including well-informed data subjects and competition among data owners.

4. An Experiment with Lueneburg Students

In an online experiment[2] with students from Lueneburg, we tested whether hypothetically offering a monetary price for Internet services instead of having users pay by surrendering their data reduced the extent of cookie fatigue. The control group could only use the artificial intelligence DeepL[3] if they paid with their data or abstained from the service altogether. Treatment Group 1 was additionally given the option to use DeepL without loss of privacy in exchange for a monetary fee, with respondents themselves able to designate their maximum willingness to pay. Treatment Group 2 could instead vote for a "campus" license of DeepL at the annual fee of EUR 10 via a student poll.

In June and July 2021, students were asked about data privacy in an online experiment in which they could hypothetically decide whether to use the Artificial Translation Intelligence DeepL. Randomly, they also had the option of paying a monetary fee instead of revealing their data. DeepL offers a free version that only allows a few texts to be translated and where the translated texts are stored for up to eight years. The latter is done to improve the software; however, there are also various service packages offered on a subscription basis for a fee where texts are deleted immediately after translation.

All students at Leuphana University Lueneburg were invited to participate in the online experiment, which they were informed of via the university's central mailing list. In addition, information about the experiment was published in the university's weekly general information medium, Leuphana Facetten. The General Students Committee (ASTA) reported on the experiment in its newsletter as well as issuing a call for students to participate. In some economic courses conducted via Zoom meeting, students were reminded of the survey or asked to participate via email. A total of 190 students opened the link to the survey, and 147 of them answered.

In the online experiment, participants could choose between different options in the first question, depending on which variant they were randomly assigned to:

- In the Control Group, if they disclosed their data via cookies, they could translate up to three Word or PowerPoint documents with a maximum file size of 5 MB. They could also build a glossary with up to 10 entries. DeepL is subject to the European Data Protection Regulation (DSGV0), so its servers are subject to European data protection law. DeepL requires consent from its users via cookies to store submitted and translated texts for up to 8 years. The purpose of the data storage is to improve the translation performance of DeepL artificial intelligence. If the user refused consent via cookies, they were not able to use DeepL. As another option, Treatment Group 1 respondents could indicate their maximum willingness to pay for the "starter" subscription with extended data protection. This option included unlimited translation opportunities of texts (by inserting it into the mask) and for five documents (Word or PowerPoint) per month. They could choose between a maximum annual fee of EUR 2, EUR 4, EUR 7, EUR 10, EUR 13, EUR 16, EUR 20, EUR 50, or EUR 72 to receive access. Treatment Group 2 had the option to vote for collective student access (campus license). Collective student access could be obtained if DeepL, or a comparably powerful translation software, was included in the next student ballot vote. If the majority of students voted for the software, all students would have access to the software via computers at the university or a VPN. After consultation with DeepL, access would be available at an annual student price of about EUR 10. If a majority of students preferred this option, all students would have to pay the additional fee. The possibility of providing access to the DeepL software in this manner has already been discussed with individual representatives of ASTA.

Figure 10 graphically depicts the decision situations for the control group and the two treatment groups. At the beginning of the experiment, participants were randomly assigned to one of the three groups. Subsequently, all three groups took part in an identical control survey.[4] Data collected included personal information: age, gender, study phase and course, semester, occupation, and financial situation. Participants were also asked about the relevance of language skills and their existing knowledge and preferences of data privacy. They answered questions on their use of fee-based, privacy-friendly services such as search engines, messenger services, and e-mail programs, as well as about current data privacy policy issues.

All participants who expressed a sufficient willingness to pay at least the EUR 10 annual fee in Treatment Group 1, or who voted for the campus license in Treatment Group 2, were given the chance to subscribe to a DeepL service package with good data protection for one year at a very low price. Any interested party would have had to pay EUR 10 out of their pocket, and the difference of the actual annual amount of just under EUR 72 would then have been paid by university budget funds. Since the potential grant requirement from this experiment was over EUR 1000, a lottery was drawn.[5]

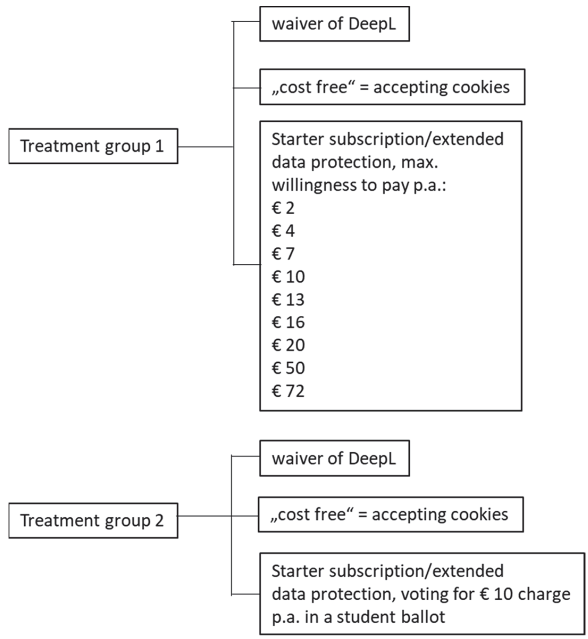

Figure 10. Experimental design.

As the online experiment used a between-subjects design, the results can be interpreted as follows, as shown in Figure 11:

- In the Control Group, potentially 79.31 percent of participants might be affected by cookie consent fatigue because they accept the violation of their privacy by accepting cookies perhaps without really wanting them. In Treatment Group 1, which worked with hypothetical willingness to pay options, the cookie "share" dropped to 30.43 percent. This effect was even stronger in Treatment Group 2 (27.91 percent), in which a price was specified that must be accepted for a transaction, as it is in markets. Admittedly, considering Treatment Group 2, only a collective demand was simulated because it would require a majority vote for sufficient willingness to pay before it would become effective. Comparing the two treatment groups with the control group, the willingness to accept cookies and thus to pay for the service by surrendering personal information decreases to a considerable extent. In the Control Group, 20.69 percent refrained from using DeepL because their privacy concerns were too great. The implicit price was too high compared to the benefits of DeepL. By expressing a positive willingness to pay, DeepL can be used without the loss of privacy (Treatment Group 1), wherein 4.35 percent of the group directly refrained from using the software. With the option of using DeepL as a campus license in the amount of EUR 10 per year (Treatment Group 2), only 2.33% of this group still wanted to abstain from DeepL completely. Compared to the Control Group, both treatment groups favored having a monetary choice to disclose or not disclose data. Microeconomically, this is not a surprising result, since an expansion of the possibility set enables utility increases, with the exception of the rare case of a corner solution. We must also note that the starter subscription also promises a higher level of service for translations compared to the "free" option. This "confounding variable" was unavoidable to improve the external validity of the experiment.
- If we compare the two treatment groups, we see that almost equal proportions opted for the third alternative: 65.21% in Treatment Group 1 with a positive willingness to pay and 69.77% with the acceptance of DeepL at an annual price of EUR 10 in Treatment

Group 2. This parallel evaluation is the other side of the coin to the reduction in the acceptance of cookies or the waiver of DeepL in the control group. However, in Treatment Group 1, 34.78% expressed a willingness to pay less than EUR 10. However, the starter version of DeepL would only be realistically available to students at the "market price" of EUR 10. The first interpretation of this result would be that the true willingness to pay of these 16 persons is not sufficient to pay a realistic monetary price in order to use DeepL without giving up privacy; the only option would be to accept cookies or to do without the service. The second interpretation would be that the participants in Treatment Group 1 did not know what a fair market price for this service would be; if there had been a price signal of EUR 10, they would also have revealed this as a willingness to pay. The second interpretation supports the assessment that the introduction of a market price as a third alternative helps subjects to implement their true preference for privacy.

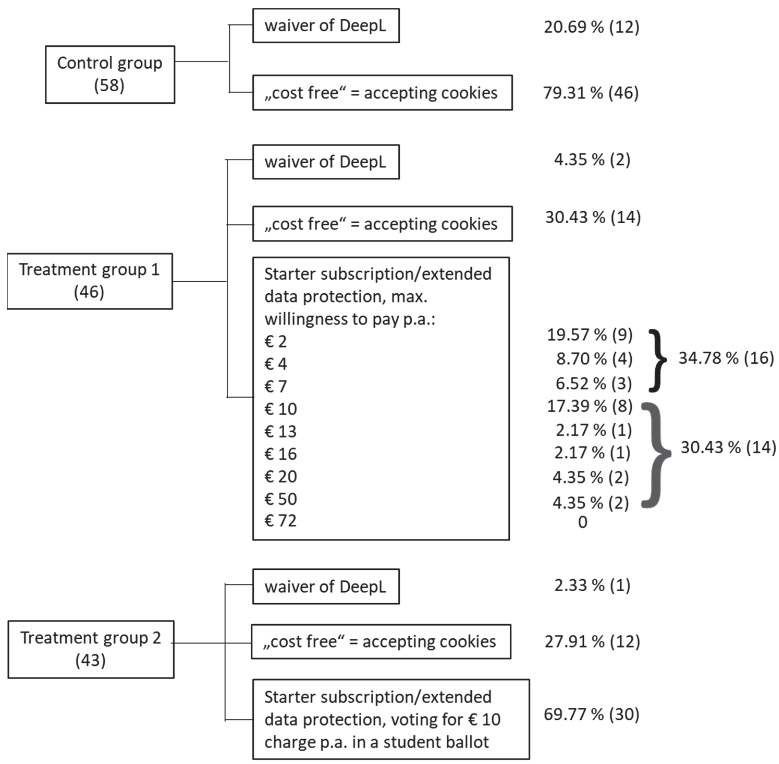

Figure 11. Experimental results.

The introduction of a monetary price for more data protection led to a decrease in the acceptance of cookies or the complete abandonment of the Internet service DeepL in both treatment groups; broader options for action for the participants benefitted them.

A total of 126 participants provided information on their student phase: 62.7 percent were in the bachelor's program, 26.98 percent were in the master's phase, 7.94 percent were doctoral students, and 2.38 percent were enrolled in the Professional School. According to their disclosed major subject, business economists with BWL/IBAE majors represented the largest groups with 13 participants, followed by 11 environmental scientists and economists whose majors included Environmental Sciences, Global Environmental, and Sustainability Studies. At the master's level, 10 respondents came from management programs, and 6 came from Public Economics, Law, and Politics (PELP). Otherwise, there were a few clusters from other majors, either identifying bachelor minors, doctoral programs, or the Professional School.

On average, respondents (Table 1) were slightly older than 25, in their fifth semester of study, worked slightly less than two days in addition to their studies, and were relatively satisfied with their student living situation—just under 7 out of 10. Of the 124 respondents, 109 grew up with German as their native language; 2 had English as their native language; and 1 each came from Belgium, Cambodia, Venezuela, Ghana, Italy, Russia, and Syria.

Table 1. Socio-demographic characteristics.

	Mean	Standard Deviation	Min.	Max.	Observations
Subject semesters	4.47	2.93	1	20	115
Age of participants	25.42	5.23	18	45	123
Average weekly working time in hours outside of studies	14.87	9.13	2	40	93
Overall life satisfaction (not satisfied at all = 0, totally satisfied = 10)	6.85	1.67	0	10	120

Own calculations with Stata 16.0.

On average, participants attended just over 9 years of school with English classes, and 22 were in an English-language school. According to the standard school grading scale[6], 118 respondents rated their overall English proficiency at an average of 1.98. They considered their reading skills to be at a 1.71 and their writing skills to be at a 2.35. Of the 85 respondents who could reveal English placement according to the European Framework of Reference, 3 indicated a B1 level, 22 indicated a B2 level, 51 indicated a C1 level, and 19 indicated a C2 level. The general financial situation of 120 respondents looked quite positive: 22.5 percent did not have to worry about their finances; 41.67 percent could save a little; and 30 percent could just about manage with their budget. Only seven participants, 5.83 percent, never had enough money.

The relevance of English skills in studies and in private life is shown in Table 2. Foreign languages other than English played almost no role. In study, English skills were frequently or even daily relevant for two-thirds of the participants. The need to read English-language texts was particularly strong, while the need to write a thesis in English was relatively less important. We used the weights 4 for "daily", 3 for "frequently", . . . , and 0 for "never", In summing up these values over all study-relevant needs, the result was a mean value of 13.14, i.e., an average of a 2.6 per need group. In the private sector, "often" was named the most frequently, and "rarely" second most frequently. The private relevance for English language skills thus seems lower than the student relevance.

The questionnaire also recorded preferences on data privacy; on legal knowledge of data privacy; on the actual use of fee-based, data privacy-friendly services; and on views of current data privacy policy issues. Preferences were indicated by putting basic rights guaranteed in Germany into a preference order, within certain limits:

- freedom to organize in a trade union;
- freedom of religion;
- right to informational self-determination;
- freedom to choose an occupation;
- protection of property;
- freedom of demonstration.

Table 2. Relevance of English skills.

	Never	Rarely	Regularly	Often	Daily	No Answer
	in Percent					
In my studies, I need English . . .						
To read the relevant literature (textbooks, journal articles, etc.)	0.83	-	8.33	25.00	65.83	-
In the course because English is the language of instruction	4.17	15.00	15.83	25.83	38.33	0.83
For written or oral exams and tests	8.33	19.17	20.83	21.67	21.67	3.33
For English-language seminar papers or term papers	8.33	18.33	14.17	25.83	31.67	1.67
For English-language theses (bachelor's thesis/master's thesis/dissertation/paper)	20.00	10.83	8.33	10.00	35.00	15.83
In private settings (travel, families, friends) do I need to know English?	0.83	19.17	27.50	35.83	16.67	-

A total of 120 answers. Own calculations with Stata 16.0.

Of 115 respondents, 40 ranked the right to informational self-determination first, and an additional 23 ranked it second. The majority thus put the fundamental right to informational self-determination, which underlies data protection, very near the front of their preferences.

To generate a measure of preference order, if the right to informational self-determination was ranked first, it was weighted by a factor of 1. If it was ranked second, it was weighted by a factor of 0.8. If it was ranked third, it was weighted by a factor of 0.6. If it was ranked sixth or last, it was weighted by a factor of 0. On average, a ranking of 0.7 was obtained with a standard deviation of 0.29 out of 115 observations.

Six legal statements were introduced in the questionnaire, and respondents were asked to check for correctness. Statements 3 and 5 were incorrect, and the remaining four were correct. If the number of correct statements was summed up, an indicator of the knowledge of data protection law was obtained. On average, a knowledge indicator of 3.26 was obtained, with a standard deviation of 1.1, minimum of 0, and maximum of 6. Anyone with data privacy concerns can already use paid services, which are much better at respecting the privacy of users than the "free" services are. A total of 4 participants used paid search engines, 21 used paid messenger services, and 32 used paid e-mail management programs.

Table 3 shows the participants' views on current privacy policy issues. In line with the high preference for the fundamental right of informational self-determination, all statements advocating high data protection were rated as very good or at least useful by many participants. It is interesting to note that the two conceivable innovations of ePrivacy, default setting via browser and obligation to provide paid alternatives when cookies are used, were still met with approval, but the latter to a significantly lesser extent.

Another question was whether respondents who can be shown to have consciously chosen DeepL differed from those who rejected DeepL when controlling for group characteristics. Table 4 shows this for feasible mean comparisons. Only the following mean differences were significant:

- Older students were more likely to choose DeepL than younger students.
- Increasing relevance of English skills for theses and in private life increased the willingness to take up a DeepL offer.
- Better English language writing skills increased the demand for DeepL.
- Higher perceived relevance of the fundamental right to informational self-determination also contributed to more DeepL.

Table 3. Opinions on data protection policy.

	Unnecessary	More Costs Than Benefits	Neutral	Useful	Very Good	Observations
	In Percent					
Data of European users may only be used in the USA according to European standards	0	7.27	9.09	31.82	51.82	110
Infection control software, such as the Corona-Warn app, may only be approved under valid, strict data protection	3.60	14.41	16.22	18.92	46.85	111
Consent to the use of cookies may only be obtained via an opt-in option (the user must explicitly allow data use)	2.70	11.71	11.71	30.63	43.24	111
Individual privacy preferences should generally be able to be set via the browser; the case-by-case consent to data use would then no longer apply	1.82	4.55	15.45	33.64	44.55	110
In addition to the free use of Internet services through the disclosure of data, every user should also be given the opportunity to use the services by paying a fee instead of disclosing data.	3.77	7.55	25.47	29.25	33.96	106

Own calculations with Stata 16.0.

Cross-tabulations with various dummy variables such as gender, native language English, correct legal knowledge, or use of various paid services did not lead to any significant correlations, so their reproduction was omitted.

Table 5 describes the partially significant results of the logit estimates to explain why experiment participants chose to accept cookies. Additional non-significant results can be found in Appendix B. According to Model 1 of Table 5, the probability of accepting cookies with an average marginal effect decreased by slightly more than 50 percentage points when a decision was made in Treatment Group 1 or Treatment Group 2 compared to the Control Group. These highly significant probabilities even increased to about 75 percentage points when controlling for participant-specific effects (Model 3 and 4). In most cases, these effects were completely insignificant (see Appendix B) or were nonrandom only for some variables in Models 2–4 (Table 5). As the need to read English-language texts during study increased, the probability of accepting a cookie decreased: a participant who needs to read English-language literature regularly instead of infrequently, or often instead of regularly, was ceteris paribus 34 percentage points (pp) less likely to choose cookies; however, this relationship was only different from zero at the 10 percent confidence level. If the relevance of English-language exam units increased by one unit, at the 5 percent significance level, the probability of acceptance increased by 25 pp. From an economic theory perspective, it is difficult to find an explanation for the opposing effects. Model 3 suggests that one more year of English language schooling leads to a small average marginal effect of 5 pp (error probability below 5 percent). With respect to current discussions on data privacy policy, according to Model 4, there was a one unit higher endorsement: (a) that data of European users in the USA may only be used according to European standards would increase cookie acceptance by 10 percentage points; (b) that cookie consent may only be obtained as opt-in options would decrease cookie acceptance by 12 pp; and (c) that a service must be offered for a fee in addition to fee-free data use would decrease cookie acceptance by a very small 2 percentage points; however, these effects are at best only at the 5 percent level different from zero. Essentially, however, it must be noted that cookie acceptance is driven down by the two treatments. Overall, confounding factors seemed to play a minor role.

Table 4. Mean comparisons.

		Decision		T-Values	Observations For/Against
		For DeepL	Against DeepL		
Age?		26.32	23.13	−2.45 ***	37/24
Subject semester?		4.68	4.25	−0.47	34/24
Working hours per week?		15.4	15.4	0.062	30/18
Years of Schooling in English?		8.89	9.42	0.725	35/24
Sufficient budget?		2.86	2.82	−0.180	22/36
Overall student satisfaction?		6.97	7.00	0.057	37/23
Relevance of English	Reading literature	4.77	4.58	−1.339	35/24
	During courses	3.80	3.9	0.230	
	Exams	3.20	3.30	0.253	
	Writing term papers	3.57	3.71	0.658	
	Writing theses	2.74	2.66	−0.144 **	
	Private settings	0.23	0.08	−1.462 **	
Years of schooling in English		8.89	9.42	0.725	35/24
English proficiency in school grades	Overall	2.00	1.65	−1.510	35/23
	Reading	1.69	1.52	−0.770	
	Writing	2.4	1.9	−2.071 **	
Relevance of informational self determination		0.76	0.61	−2.010 **	35/24
Correct answers on data protection law		3.47	3.30	−0.574	34/23
Data protection policy	European data standards in the USA	4.85	4.73	−0.313	34/22
	Infection control software only under strict data protection	4.24	4.59	0.781	34/22
	Consent to cookies only as an opt-in option	4.32	5.09	1.972 *	34/22
	Privacy preferences via browser	4.97	4.45	−1.284	34/22
	Additional obligation to offer against payment	4.09	4.32	0.545	33/22

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$; own calculations with Stata 16.0.

The estimates of Table 5 still need to be evaluated for their model goodness. To measure their explanatory power, one can ask what percentage of the observations would have been correctly classified (cookies predicted to be rejected/actually rejected or cookies predicted to be accepted/actually accepted) by picking observations quasi-randomly compared to the prediction of the model. In Model 1, the proportion of those correctly predicted increased from 48.9 to 74.2%, for Model 2 from 51.5 to 79.8%, for Model 3 from 50.8 to 80 %, and for Model 4 from 47.1 to 77.9%; in total, a not insignificant explanatory power in each case. Furthermore, as a rule of thumb, the appropriateness of the logit model can be measured by relating the number of cases for the lower value of the variable to be explained, in this case, acceptance of cookies versus rejection, to the number of explanatory variables (without the constant) and trusting in the appropriateness if a value of 10 or greater is given (Van Smeden et al. 2016). Models 1 and 3 reached this threshold, whereas models 2 and 4 did not. In Model 3, there was also evidence of collinearity, as the covariance value between schooling in an English-speaking country and studying at an English-speaking university was 0.16. For all other variables, the covariance values remained well below 0.1, so collinearity probably did not play a role there.

Table 5. Logit-regression cookie decisions.

		Model 1	Model 2	Model 3	Model 4
Treatment Group 1 = 1		−0.54 *** (0.05)	−0.67 *** (0.04)	−0.72 *** (0.03)	−0.73 *** (0.03)
Treatment Group 2 = 1		−0.57 *** (0.05)	−0.83 *** (0.03)	−0.76 *** (0.03)	−0.82 *** (0.02)
Relevance of English	Reading literature		−0.34 * (0.19)		
	During courses		−0.09 (0.27)		
	Exams		0.25 ** (1.37)		
	Writing term papers		−0.15 * (0.20)		
	Writing theses		0.09 (0.37)		
Years of schooling in English				0.045 ** (0.09)	
Stay in English-speaking school?				−0.21 (0.32)	
Study at English-speaking university?				0.008 (0.49)	
Data protection policy	Data of Europeans in the USA only according to European standards				0.10 * (0.31)
	Infection control software, such as the Corona-Warn app, may only be approved under valid, strict data protection				0.26 (0.16)
	Consent to cookies only as an opt-in option				−0.12 ** (0.11)
	Privacy preferences via browser, case-by-case consent not required				−0.07 (0.14)
	In addition to free use, obligation to offer against payment				−0.02 * (0.16)
Constant–odds ratios		3.83 *** (1.25)	371.33 *** (756.13)	1.29 (0.786)	25.72 ** (42.48)
Wald test (X^2, (p-values))		30.99 *** (0.000)	23.56 *** (0.001)	30.22 *** (0.000)	33.50 *** (0.00)
Correctly classified with constant/with full model in percent		48.9/74.2	51.5/79.8	50.4/80.0	47.1/77.9
Events per variable (EPV)		31	6.9	11.4	7
Observations		147	99	115	104

Dependent variable: cookie accepted = 1, otherwise = 0. Values marginal average effects, robust standard errors in parentheses; * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Own calculations with Stata 16.0. English native language omitted.

5. Summary and Conclusions

When using Internet services, private households often feel compelled to agree to the use of cookies in order to be able to use the services offered for “free”. This is known as “cookie consent fatigue”. They pay for services via the implicit price of providing data about themselves. They may not even want these data-based transactions, or they may prefer to be charged a monetary fee.

A legislative process is currently ongoing in the European Union to add a new privacy regulation to the 2018 General Data Protection Regulation. One innovation of the new regulation would be that service providers on the Internet, who currently must obtain the consent of their users via an opt-out provision, must always provide a fee-based alternative without disclosing data.

A simple economic exchange model shows that users, as data subjects, are basically faced with the choice of paying a monetary price for the service and preserving their privacy, or putting privacy preferences second and using Internet services "for free" while accepting a loss of utility in the form of reduced privacy. If we assume that a person is a data user and thus provides an Internet service, and also acts as a data subject who perceives the surrender of privacy as a loss of utility, a market equilibrium is reached with a utility-maximizing demand for data privacy and an optimum supply of Internet services for which a charge is made. The individual demand for data privacy only coincides with the socially optimal demand if there is competition in the markets for data and Internet services, or if users are sufficiently informed. If the current data privacy policy does not sufficiently protect the privacy of users, an obligation to offer services for a fee can make users better off than the current legal system.

In an online laboratory experiment with students at Leuphana University, the focus was on data privacy while using the artificial intelligence DeepL, which can translate foreign-language texts into many languages. Today, DeepL offers several usage options. One option is to use the translation function to a limited extent free of charge, but users "pay" for usage by agreeing to DeepL storing and reusing the texts entered for up to eight years. If you refuse this consent, free use is not possible. DeepL also offers paid subscriptions, where users' texts are immediately deleted.

All students at Leuphana University in Lueneburg were invited to participate in the online experiment. A total of 190 students opened the link to the survey and 147 of them answered. The Control Group received exactly the same conditions as DeepL without payment: exposure of data for eight years with limited possibility of translation or no translation service if users "insisted" on the privacy of their data. In Treatment Group 1, respondents could indicate their maximum willingness to pay for the so-called starter subscription with extended data protection as an additional option by choosing between different maximum annual fees. In the Treatment Group 2, there was the other option of voting for collective student access to the starter subscription of DeepL at an annual price of EUR 10 (campus license), with access available via university computer or VPN. If this option was accepted by the majority of students in a student vote, all students would have to pay the additional fee. To motivate the participants realistically, they could get the starter subscription available on the market and had to pay only EUR 10 per year with the university supplementing the remainder of the actual costs.

In this between-subjects design, cookie consent fatigue may have affected almost 80 percent of participants in the Control Group, while in Treatment Group 1, the cookie "share" dropped to just over 30 percent, and even more so in Treatment Group 2, by about 28 percent. Compared to the Control Group, both Treatment Groups showed that the option of not only being able to choose between not using cookies or using them with a low level of data protection, but also being able to pay directly for the service, allows users' preferences to take better effect. The descriptive values, the bivariate tests, and the limited feasible logit estimates suggest that the decrease in cookie consent fatigue cannot be explained by a different composition of the three subgroups but are "caused" solely by the interventions of the treatment.

Limits to the validity of the experiment are, of course, that students certainly deal differently with the Internet and with data protection than the general population, and that translation software is likely to be of greater importance to them. It also remains to be considered that the starter subscription has a higher scope of services for translations compared to the "free" scheme. With the student vote, one makes the demand for DeepL a collective good, although translation aids are certainly a private good; however, it is only through collective provision that one arrives at annual fees that are potentially accepted by students.

In summary, in the theoretical model under competition the optimal demand for privacy would be realized. With the obligation of ePrivacy regulation to declare prices for allowing privacy, optimal privacy demand is made possible. Compared to the status quo of presumed cookie consent fatigue, there is an improvement in the sense that users receive more choices. The experiment with Leuphana students shows this very clearly; however, the experiment also shows that the price for privacy is the decisive parameter. If the service providers charge access fees at an astronomical price, the regulatory mandate of choice does not help much. Only if there is sufficient competition in markets for data and for online services will there be an improvement.

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Appendix A

Optimal Data Protection

Let the production function of the data owner be

$$x = Ad^{\beta}. \tag{A1}$$

The utility function of the data subjects can be written as

$$U(x, D - d) = x^{\alpha}(D - d)^{(1-\alpha)}. \tag{A2}$$

This results in the optimization problem:

$$\max_{x,d} x^{\alpha}(D - d)^{(1-\alpha)} \text{s.t.} x = Ad^{\beta}, \tag{A3}$$

which leads to the Lagrange function:

$$\mathcal{L} = x^{\alpha}(D - d)^{(1-\alpha)} + \lambda(x - Ad^{\beta}) \tag{A4}$$

After forming the first-order conditions and algebraic rearrangements, we obtain

$$d^{*} = \frac{\alpha\beta D}{1 - \alpha(1 - \beta)} \qquad x^{*} = A\left(\frac{\alpha\beta D}{1 - \alpha(1 - \beta)}\right)^{\beta}. \tag{A5}$$

Decisions of W as Data Owner and Data Subject

Data owners as profit-maximizing producers optimize:

$$\max_{x,d} px - td \qquad \text{s.t.} x = Ad^{\beta}, \tag{A6}$$

Inserting the constraint yields

$$\max_{d} pAd^{\beta} - td. \tag{A7}$$

This determines the optimal data demand

$$d^{**}_{Demand}(t,p) = \left(\frac{\beta p A}{t}\right)^{\frac{1}{(1-\beta)}}, \tag{A8}$$

and this result inserted into Equation (A1) leads to the profit-maximizing supply of Internet services:

$$x^{**}_{Supply}(t,p) = A\left(\frac{\beta p A}{t}\right)^{\frac{\beta}{(1-\beta)}}. \tag{A9}$$

It arises as profits of the data owner:

$$\pi(t,p) = px_{Supply} - td_{Demand}. \tag{A10}$$

Equations (A8) and (A9) inserted into (A10) as well as transformed leads to the equation

$$\pi(t,p) = (1-\beta)(Ap)^{\frac{1}{(1-\beta)}}\left(\frac{\beta}{t}\right)^{\frac{1}{(1-\beta)}}. \tag{A11}$$

As a data subject, W earns income I from profit as a data owner and from giving up data,

$$I = td + \pi(t,p). \tag{A12}$$

which is remunerated at t per unit.

Assuming that at most the data set D can be "used" by the data subject, her utility maximization problem arises:

$$\max_{x,d} U(x, D-d) = x^{\alpha}(D-d)^{(1-\alpha)} \text{s.t.} px = td + \pi(t,p). \tag{A13}$$

From the application of the usual Lagrange maximization follows the utility maximizing data set:

$$d^{**}_{Supply}(t,p) = \alpha D - \frac{(1-\alpha)\pi(t,p)}{t} = \alpha D - \frac{(1-\alpha)(1-\beta)}{\beta}\left(\frac{\beta p A}{t}\right)^{\frac{1}{(1-\beta)}} \tag{A14}$$

and as utility-maximizing demand for Internet services:

$$x^{**}_{Demand}(t,p) = \frac{\alpha}{p}(tD + \pi(t,p)) = \frac{\alpha t}{p}\left(D + \frac{(1-\beta)}{\beta}\left(\frac{\beta p A}{t}\right)^{\frac{1}{(1-\beta)}}\right). \tag{A15}$$

Equilibria in data and Internet markets prevail if Equations (A8) = (A14), and (A9) = (A15), respectively, are satisfied; the first condition ensures market clearing in the data market, and the second in the market for Internet services. Calculating the market clearing in the data market, the equilibrium data price is as follows:

$$t^{**} = \beta A\left(\frac{1-\alpha(1-\beta)}{\alpha\beta D}\right)^{(1-\beta)} p. \tag{A16}$$

The same is true if we calculate the market clearing in the Internet market.

Solving Equation (A16) for p and substituting this into the profit-maximizing supply for Internet services (Equation (A9)) (alternatively into the optimal demand) yields

$$d^{**} = \frac{\alpha\beta D}{1-\alpha(1-\beta)}, \tag{A17}$$

which is identical to the welfare-optimal quantity in the data market d* from Equation (A5).

Appendix B

Table A1. Logit-regressions cookie decisions—non-significant confounders.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment Group 1 = 1	0.07 *** (0.04)	0.03 *** (0.02)	0.07 *** (0.04)	0.05 *** (0.03)	0.06 *** (0.03)	0.08 ** (0.04)	0.08 *** (0.04)	0.07 *** (0.04)
Treatment Group 2 = 1	0.06 *** (0.03)	0.06 *** (0.04)	0.07 *** (0.04)	0.05 *** (0.03)	0.05 *** (0.03)	0.08 *** (0.05)	0.07 *** (0.04)	0.07 *** (0.04)
Master program, yes?	1.02 (0.51)							
PhD-candidate, yes?	0.62 (0.43)							
Professional school, yes?	1.47 (1.95)							
Age?		1.03 (0.07)						
Women yes, men and divers no		0.81 (0.50)						
Subject semester?		1.00 (0.08)						
Working hours per week?		0.97 (0.03)						
Relevance of budget constraint?		0.58 (0.24)						
Overall life satisfaction?		0.95 (0.15)						
Sum of English relevance?			0.98 (0.04)					
English proficiency in school grades: overall				0.94 (0.48)				
English proficiency in school grades: reading				1.31 (0.54)				
English proficiency in school grades: writing				1.37 (0.50)				
Common European Framework of Reference for Languages (CEFRL)					0.92 (0.90)			
Sum of the correct answers on data protection law						0.78 (0.15)		
The basic right to informational self-determination–Aggregate value							1.04 (0.79)	
Use of fee-based search engines?								0.60 (1.22)

Table A1. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Use of fee-based messenger services?								0.93 (0.62)
Use of fee-based e-mail programs?								0.40 (0.25)
Constant	5.78 *** (2.59)	39.06 * (84.50)	7.00 *** (4.87)	2.31 (1.67)	8.10 *** (3.71)	10.24 *** (7.29)	4.61 ** (3.17)	6.73 *** (2.90)
Wald test (X^2, (p-values))	32.95 *** (0.000)	26.91 *** (0.001)	31.25 *** (0.000)	41.53 *** (0.00)	38.34 *** (0.000)	29.76 *** (0.00)	29.68 *** (0.000)	30.93 *** (0.00)
Observations	126	84	120	118	115	112	115	115

Dependent variable: cookie accepted = 1, otherwise = 0. Values odds ratios, robust standard errors in parentheses; * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$. Own calculations with Stata 16.0.

Notes

1 Especially in the long run, it is plausible that more data will lead to increasing marginal returns. In extreme cases, only one data owner will "survive" and a monopoly will emerge. This model variant would lead to the regulation of a natural monopoly. In this model, the focus is solely on data protection policy under competition.

2 The LimeSurvey software was used for the online experiment.

3 DeepL is a translation software that allows simultaneous translation of text sections, Word documents, and PowerPoint files, using text from users. Translations are available from English, French, German, and Spanish, as well as from many less-widely used languages. The extensive glossary function allows for individual improvement of one's own texts. Even simultaneous grammatical optimization is possible. In the experiment, two tutorial videos were created for DeepL that could only be accessed via YouTube with a participant-specific link.

4 The questionnaire can be requested from the author.

5 According to the available funding and the conditions mentioned above, grant beneficiaries were randomly selected and announced via the institute's homepage using the name–birthday abbreviation recorded in the survey. Eligible individuals not drawn were notified that they were on a waiting list. Only one person (from the waiting list) wanted to "take" the grant, but has not yet claimed it.

6 Best grade = 1, . . . , worst grade = 6.

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economies

Article

Actor Fluidity and Knowledge Persistence in Regional Inventor Networks

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Abstract: The development of inventor networks is characterized by the addition of a significant number of new inventors, while a considerable number of incumbent inventors discontinue. We estimated the persistence of knowledge in the inventor networks of nine German regions using alternative assumptions about knowledge transfer. Based on these estimates, we analyzed how the size and structure of a network may influence knowledge persistence over time. In a final step, we assessed how persistent knowledge as well as the knowledge of new inventors affect the performance of regional innovation systems (RIS). The results suggest that the knowledge of new inventors is much more important for RIS performance than old knowledge that persists.

Keywords: innovation networks; knowledge; R&D cooperation; patents; persistence

JEL Classification: O3; R1; D2; D8

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1. Fluidity of Network Actors and Regional Knowledge

Well-functioning regional innovation systems (RIS) are characterized by a high level of knowledge transfer and the division of innovative labor (Asheim et al. 2019). This means that the relationships between actors within and outside a region can play a key role in the development of the regional knowledge base and the performance of RIS. The network of relationships among actors that are involved in innovation processes may, therefore contribute to explaining the scope, nature, and efficiency of regional innovation activity (Ejermo and Karlsson 2006; Jackson 2008; Cantner and Graf 2011).

Innovation networks are not static at all and may be characterized by rather high levels of newly emerging actors, while many incumbent actors withdraw from regional innovation processes. The rather few empirical studies that have analyzed the dynamics of actors and their links in innovation networks (Fritsch and Zoellner 2020; Fritsch and Kudic 2021; Greve et al. 2009; Ramlogan and Consoli 2014) have shown surprisingly high levels of new and existing actors as well as newly established and terminated links. For example, Fritsch and Zoellner (2020), in an analysis of regional inventor networks, found that more than 78 percent of all inventors were only present in one three-year period, 14.51 percent were active in two periods, and only about 7 percent appeared in networks for more than two successive periods. Only 9.7% of all links between inventors could still be found in the successive period. Analyzing the effect of fluidity on the structure of the inventor networks, Fritsch and Zoellner (2020) found some statistically significant relationships with the share of the largest network component and the share of isolates. Relating the levels of fluidity to the performance of networks in terms of the number of patents per R&D employee (patent productivity) suggests the positive effects of new actors and links.

The consequences of this high level of actor-turnover or 'fluidity' for the network and the performance of the respective regional innovation system (RIS) have largely been unexplored. In general, the high level of fluidity in inventor networks can be regarded as an indication that there are benefits of switching cooperation partners despite considerable transaction costs. These transaction costs involve the effort of establishing new links as well as sunk costs related to abandoning an established link. One specific benefit may be access to new knowledge through newly established links.

The empirical analyses of the performance of inventor networks in German regions by Fritsch and Zoellner (2020) showed mixed results for the relationship between the turnover of inventors with the performance of the respective RIS measured by the level and change in the number of patents per R&D employee (patent productivity). While there was a significantly positive relationship of the share of new inventors with RIS performance, the relationship of patent productivity with the share of discontinued actors was also positive, but showed a negative effect for the share of discontinued links (Fritsch and Zoellner 2020). A possible explanation for the positive relationship between RIS performance and the share of new actors is the additional knowledge that the new inventors add to the system. A reason for the non-negative relationship between the share of discontinued actors and RIS performance may be that the knowledge of discontinuing actors remains with their cooperation partners, who continue in the network.

Based on the data used by Fritsch and Zoellner (2020), this article investigated two potential sources of knowledge, namely persistent knowledge and the knowledge of inventors who newly entered inventor networks in nine German regions. We tried to assess how much of the knowledge of the inventors that disappeared from an inventor network may still be available because it has been passed onto continuing network inventors during their cooperation. For this purpose, we identified the inventors that cooperated with discontinuing inventors and determined whether these co-inventors were included in the network in the subsequent period. We assumed that at least part of the knowledge of a discontinued inventor was still available if the co-inventors were still within the network. Based on alternative assumptions about the amount of knowledge transfer among co-inventors, we estimated the share of knowledge that is still available in the network and analyzed the role of network characteristics that measure the frequency relationships and the integration of inventors in larger components for knowledge continuity. Our analyses suggest that there is a higher level of persistent knowledge in a network that is well-integrated and has a large average component and team size, with relatively high shares of inventors in the largest component, and low shares of isolates. Finally, we analyzed the effect of persistent knowledge and the knowledge of new inventors on the performance of RIS. The results suggest that the knowledge of new inventors is much more important for RIS performance than old knowledge that persists.

Our analyses contribute to the research into the role of inventor networks and their dynamics in regional innovation processes (Cantner and Graf 2011). In particular, our results help understand the capacity of networks not only to generate new knowledge and to disseminate it, but also to retain that knowledge in case the respective inventors leave the network. Moreover, the results link to the literature on brain drain, migration, and innovation (Bahar et al. 2020; Lissoni 2018).

The rest of this paper is organized as follows. In Section 2, we first discuss the cost and the benefits of changing actors and relationships in innovation networks). Section 3 introduces the data and indicators, and in the following section, and we assess the effect of inventor fluidity on the continuity of knowledge in the network in Section 4. We then investigate to what extent the level of knowledge continuity is related to characteristics of the respective inventor network in Section 5. The effect of knowledge persistence on the performance of RIS is investigated in Section 6. The final section summarizes the results and conclusions.

2. Actor Turnover, Knowledge Persistence, and Network Characteristics

Knowledge, especially non-codified tacit knowledge, is of fundamental importance for innovations and the performance of RIS (Wang and Wang 2012). Hence, the performance of RIS may suffer if an inventor discontinues their activity and is no longer part of the network. However, if an inventor disappears from a network, their knowledge is not necessarily lost, but may persist in the network because it has been transferred to co-inventors who are still part of the network during the period of their cooperation. Cooperative activities, then, not only lead to the generation of new knowledge, but they may also ensure that knowledge of discontinued inventors persists (Schilling and Phelps 2007). Keeping the knowledge of discontinuing inventors available may be an important way of how networks affect the performance of the respective RIS. If knowledge is transferred by co-inventorship, then the size of inventor teams should be important for the persistence of knowledge (see, Tang et al. 2008). The larger the inventor team, the higher the propensity that one or more of the inventors from the original team who possess at least parts of the discontinued inventor's knowledge will be available in a successive period. Assuming that the knowledge of inventor teams may also be passed on to inventors who are linked to other inventors but not directly linked to a certain invention, this argument may be extended to the respective network component (see, Fronczak et al. 2004); inventors who are directly and indirectly linked. Hence, RIS with larger inventor teams and larger network components should benefit from a higher intensity of knowledge exchange that may keep the knowledge of discontinuing inventors available. Fritsch and Kudic (2021), in an analysis of inventor networks in German laser technology, found that inventors who became key players in the network had frequently been members of the ego network of an inventor who assumed a role as a key player in a previous period. For these reasons, one may expect:

Hypothesis 1: *The larger the size of inventor teams, the more the knowledge of discontinuing inventors can be stored in the network and is able to persist.*

Hypothesis 2: *The larger the size of a network's components, the more the knowledge of discontinuing inventors can be stored in the network and is able to persist.*

It may, however, not only be the size of a network's components, but also the density of relationships that define a network's level of cohesion that is important for the amount of knowledge that is transferred within a network (Ahuja 2000; Uzzi and Spiro 2005; Jackson 2008). Cohesion measures the clustering or density of a network (Burt 2001; Cowan and Jonard 2004; Fritsch and Kauffeld-Monz 2010), whereas range describes the average distance between inventors within a network. If a network shows a high level of clustering and a low range, this indicates small world properties. Since more ties between inventors should lead to increased knowledge transfer, the knowledge of discontinuing inventors should more easily persist in dense networks.

Hypothesis 3: *The higher the cohesion of a network, the more the knowledge of discontinuing inventors can persist and is available in later periods.*

It is plausible to expect that the performance of a RIS will benefit if knowledge of the discontinuing inventors persists and remains available. Another important source of knowledge that should be important for RIS performance is the entry of new inventors that add new knowledge. Based on these considerations it is expected that:

Hypothesis 4: *The more the knowledge of discontinuing inventors remains available in a network, the better the performance of the respective innovation system.*

Hypothesis 5: *The larger the share of new inventors who enter the network and make their knowledge available, the better the performance of the respective innovation system.*

It is, however, an open question of which of the two sources of knowledge—new knowledge or knowledge from previous periods that persists—has a more pronounced effect on RIS performance. We will try to answer this question in our empirical analysis.

3. Data and Spatial Framework

We analyzed inventor networks based on patent applications as documented in the DEPATISnet database (www.depatisnet.de, accessed on 4 October 2022) maintained by the German Patent and Trademark Office (*Deutsches Patent- und Markenamt*). Compared to the OECD RegPat data, these data are considerably more comprehensive since it also contains the complete set of patents that has only been filed at the German Patent Office and not the European Patent Office, so are not included in the RegPat data. For example, the number of patents that is recorded in RegPat for the same regions and period of time was only about 53% percent of the number of patents that we found in our database. Quite remarkably, this share varies considerably across the regions of our sample. We spent rather considerable amounts of effort and time to identify the same inventors named in several patents, an issue that is of key importance for the topic of our analysis. This included correcting typing errors and identifying variant spellings of an inventor's name as well as—in some cases—detailed web-based research.

The key assumption in constructing networks of inventors is that inventors who are named in the same patent document know each other and have worked together in generating the respective invention (Balconi et al. 2004). More specifically, we assumed that all of these links between co-inventors were of the same intensity so that all connections were weighted equally. Patents were assigned to regions based on the information about the residence of the inventor (Breschi and Lissoni 2001; Raffo and Lhuillery 2009). If some of the inventors named in a patent had residences in different regions, we divided the respective patent by the number of inventors involved and assigned only that fraction to the region that corresponded to those inventors who had their residence in the region. If, for example, a patent had three inventors and only two inventors had their residence in the region, we assigned two thirds of the patent to the region. Hence, the number of regional patents may not always be a whole number.

As an alternative to inventor networks, one could analyze the cooperative patenting activities between organizations that apply for a patent (e.g., public research institutes and firms). This would be based on the assumption that the relevant knowledge is retained mainly in the researching organizations and not with the inventors. Such cooperative relationships between organizations can be identified in the patent statistics if the patent document names several organizations as applicants. There is, however, no information is available in such cases that identifies the partner with which an individual inventor that is listed in the patent document is affiliated. The total number of patents that had several applicants (over all regions and time periods) in our data amounted to 2748 cases. This is only a rather small share (0.57% percent) of all patent applications. This implies that the largest part of cooperative efforts by inventors occurs within the same organization. Given the small share of co-applications, we believe that an analysis of cooperative relationships at the level of inventors provides a much more comprehensive picture of knowledge flows in a RIS than investigating the co-applications of organizations[1]. Such an analysis assumes that the relevant knowledge is represented by the inventors rather than by the organizations with which they are affiliated.

We constructed the regional inventor networks in nine German planning regions for five three-year periods over a time span of 15 years. These periods were 1994–1996, 1997–1999, 2000–2002, 2003–2005, and 2006–2008. Using longer time-periods (e.g., five year periods) does not lead to substantially different results. Patents were assigned to time periods according to the year they were filed. Five of these regions were located in East Germany, the former socialist GDR, and four regions were in West Germany (see Figure 1). Planning regions are functional spatial units that are somewhat larger than labor market regions or travel-to-work areas. They normally comprise several NUTS3-level districts, namely, a core city and its surrounding area. While districts are administrative geographic units, planning regions are more often used for spatial analysis and policy development, particularly regarding public infrastructure planning.

Figure 1. The regional framework of the analysis.

We considered planning regions as more suitable than districts for an analysis of regional innovation systems (RIS) for two reasons. First, a single district, particularly a core city, is probably too small to include the most important inventors of innovation-related local interaction. The second reason is of a methodological nature: Since patents are assigned to the residence of the inventor, taking only a core city as a region would lead to an underestimation of patenting activity since many inventors who work in cities have their private residence in surrounding districts. Looking at the spatial structure of the co-inventor relationships, we found that 73.4% of these interactions were with inventors located in the same planning region, and 16.8% were with inventors in adjacent planning regions. These figures clearly indicate that planning regions are a meaningful spatial category for the analysis of regional innovation processes.

The case study regions were selected to primarily fulfil two purposes. First, they were supposed to serve as a comparison of regions with a relatively high or low innovation performance. Second, the sample contained regions in East and West Germany that were similar in size and density. This allows us to make a meaningful comparison between the two parts of the country, even though this was not the focus of this paper. Aachen, Dresden, Jena, and Karlsruhe have medium level population densities, and are characterized by a RIS that has a relatively good performance. The other five regions, Halle, Kassel, Magdeburg, Rostock and Siegen, have considerably lower levels of innovation activity. Rostock and Siegen are smaller cities located in rather low-density rural areas. Halle, Magdeburg, and Kassel have larger populations than Rostock and Siegen, but they can hardly be regarded as densely populated. All regions are host to at least one university. Data on the regional number of employees in R&D are from the Establishment History File of the Institute for Employment Research (IAB, Nuremberg). Figure 1 shows the location of the nine case-study regions.

The nine regional inventor networks under inspection are quite heterogeneous with regard to the numbers of patents, inventors, ties, and components (see Table A1 in the Appendix A). All regions, except Halle and Aachen, showed a steady growth in the numbers of inventors (network size) and ties. In all regions, the number of components increased over the period of analysis. Except for Halle, all regions exhibited a total increase in the mean degree, indicating increasing interconnectedness of regional inventors (Table A1). The number of patents reached its maximum in the 2000–2002 period, followed by a decrease in the following period and an increase in the final period.

The share of co-patents increased over the observation period and made up about 90 percent in the final sub-period (Table A4). These developments of the mean degree and the increasing importance of R&D collaborations were in line with the overall trends reported in the literature (e.g., Wuchty et al. 2007; Jones et al. 2008) and indicated an increasing importance of research collaboration. Due to the increasing mean degree of the networks under inspection, one might also expect a decrease in the average path length. We found, however, an increase in the average path length in most of the networks (Table A4), which can be explained by the growing number of actors, and therefore, to an exponential increase in the number of potential cooperation partners. A further explanation could be the growing number of components (Table A1) that may also indicate an increasing variety of knowledge fields within a region.

We used two metrics for the performance of a network. The first was the number of patents per R&D employee and describes the productivity of a network in generating patentable inventions (patent productivity). The higher the level of patent productivity, the better the performance of the network in terms of generating new ideas (Fritsch 2002; Fritsch and Slavtchev 2011). The second performance indicator was the percent change of patent productivity. Table A3 in Appendix A provides the descriptive statistics for the variables and Table A5 displays the correlations between variables.

4. Inventor Turnover and Continuity of Knowledge

4.1. Inventor Turnover in Inventor Networks

In contrast to the widespread assumption that inventors and ties in networks are persistent over time, our data showed a rather high level of inventor turnover between time periods. We found that more than 78 percent of all inventors were present only in one observation period, 14.51 percent were active in two periods, and only about 7 percent appear in networks for more than two periods (Figure 2). On average, 32.34 percent of the inventors that were active in a network were carryovers from the previous period. Hence, at least 60 percent of the inventors in a regional network appeared in a sub-period for the first time, indicating that large amounts of new knowledge frequently enter the network from period to period. The share of applicants present in two successive periods was in about the same range. Taking all applicants together, the average share was 25.54%. There were, however, rather pronounced differences in this respect between the types of applicants. While the share of reappearing private persons that could not be assigned to a certain organization was rather low (14.44%), the share for organizations (firms and public research organizations) was much higher (33.85%). For larger universities, the share was close to 100%.

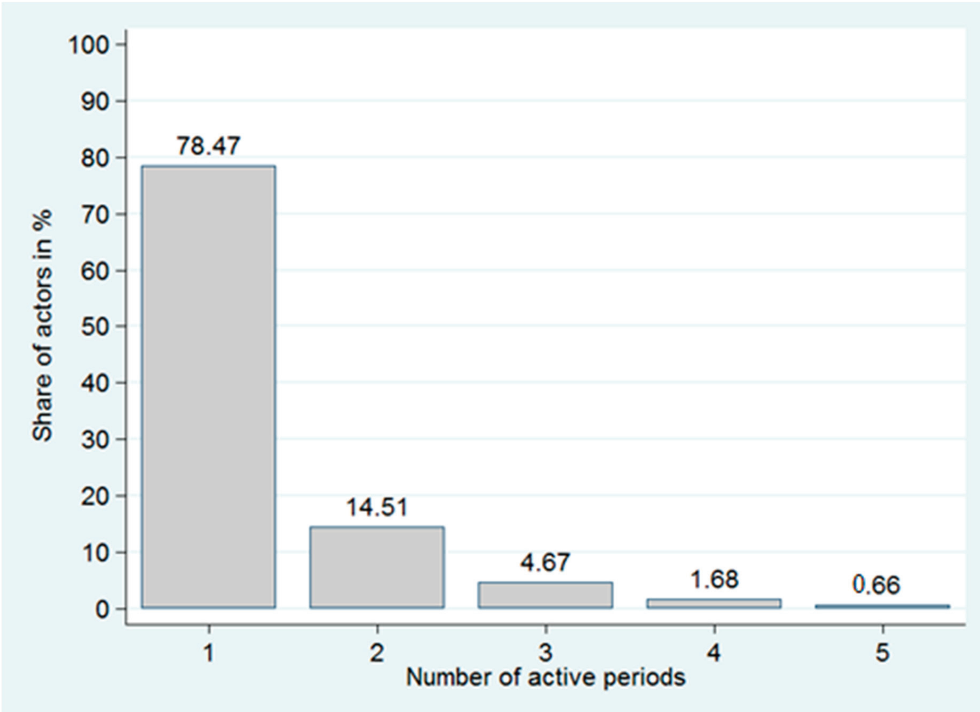

Figure 2. Share of inventors that are present in different numbers of time periods.

The persistence of links among actors was even less pronounced. We found that 83.73 percent of the links existed only in one period, 13.06 percent lasted for two periods, 2.51 percent of the links could be found in three periods, 0.52 percent in four periods, and only 0.17 percent of the links lasted over five periods. For the shares of discontinued actors and new actors in the different regions and time periods, see Table A2 in Appendix A.

The increasing share of co-patents (Table A4) indicates that the networks are characterized by a growing tendency to cooperate. Figure 3 supports this assumption. Thus, around 93 percent of new inventors—those that were not present in a previous period—entered a network in a collaboration with other inventors, while only a minor share emerged as an isolate (7%). With regard to the largest component, the share of discontinuing inventors (7.4%) was more than compensated for by the share of new inventors (9%). In the group of isolates, the share of discontinued inventors was larger than the share of newly emerging ones. These developments clearly indicate a growing level of connectivity between network inventors.

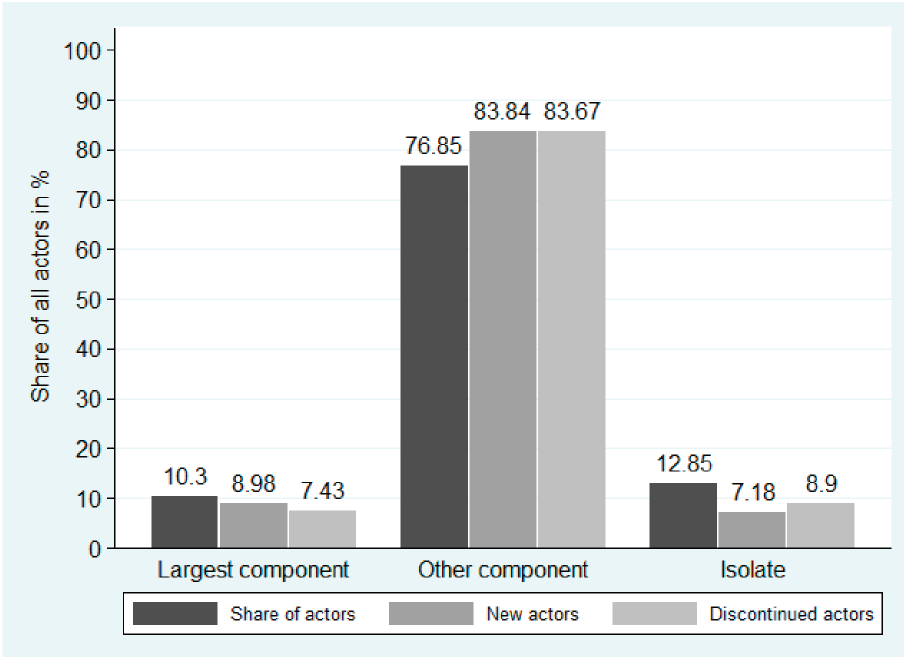

Figure 3. Positions of the newly emerging and discontinued inventors over the entire observation period.

Overall, we found that inventor networks are characterized by rapidly changing compositions of inventors and links, contradicting the transaction cost theory (Ejermo and Karlsson 2006) as well as the assumptions of Barabási and Albert (1999). The networks of our sample showed a tendency to grow continuously since the number of discontinued inventors was more than compensated for by new inventors that mainly entered with a cooperative relationship. Thus, the inventor networks under inspection showed an increasing level of connectivity over time.

4.2. Assessing the Share of Persistent Knowledge

We used several indicators to assess the amount of a discontinuing inventor's knowledge that may still be available because it has been passed onto their co-inventors in the previous period. For this purpose, we identified the co-inventors of a discontinued inventor that were still included in the network in the subsequent period. If a co-inventor of a discontinued inventor remained in the network, we assumed that at least certain parts of the patent-specific knowledge of the discontinued inventor was still available. If a discontinued inventor was involved in several co-patents, we assumed that they only transferred the knowledge specific to the patented invention and not the knowledge relevant for their other patents.

In the baseline version, we assumed that the patent-specific knowledge of a discontinuing inventor was entirely transferred to each co-inventor during the time of collaboration. We then identified the inventors who remained active in the network in the subsequent period and the knowledge that they represent. Based on this information, we finally determined the amount of persistent knowledge.

In detail, we proceeded as follows:

- We generated a list of all patents that involved regional inventors, which represents the knowledge stock of period t-0.
- If an inventor from period t-0 was still in the network in period t-1, we assigned their patents from period t-0 to them.

- The share of knowledge that is transferred between period t-0 and t-1 is the number of patents in the list from period t-1 over the total number of patents in period t-0. Since an inventor from period t-0 may not be present in t-1 but re-emerge in a later period t-2 or t-3, we ran additional models to compare the list of patents between more distant time periods as a robustness check. However, the direction and significance of the coefficients remained the same.

As robustness checks, we also calculated the share of knowledge that was transferred across periods in two alternative ways.

- The first alternative method was based on the assumption that knowledge transfer among inventors is not complete, but that inventors keep parts of their knowledge that is completely lost when they discontinue in the network. We assumed that co-inventors transferred only 50 percent of their knowledge to each co-inventor.
- In a second alternative way of calculating the transferred knowledge, we assumed that the complete patent-specific knowledge was equally divided among all co-inventors. Hence, if there are, say, three (five) co-inventors of a patent, each co-inventor represents one third (one fifth) of the new knowledge that is behind the patent. In the next step, we checked which inventors remained active within a network in the next period. If only one inventor remained active in the subsequent period, then one third (one fifth) of the knowledge remains available. In the case of two remaining inventors, two thirds (two fifths) of the knowledge is available. The rest of the procedure followed the previous model. The idea behind this second alternative method of estimating the amount of knowledge transfer is that there should be more specialization and division of labor in larger teams so that the knowledge of an inventor may not be completely transferred to all team members. Moreover, larger teams may be characterized by a rather pronounced division of labor between specialists, with limited understanding, who are only able to only absorb parts of the knowledge of their co-inventors.

Based on the first method of estimating the transfer of knowledge between periods that assumes that the knowledge of an inventor is completely transferred to all of their co-inventors, we found that between 30.1% and 92.7% of the knowledge from one period remained in the network in the subsequent period despite high levels of fluidity (Table 1)[2]. This share does, however, vary considerably across time periods and regions. If we assumed an only 50% transfer of knowledge, the share of remaining knowledge ranged between 18.9% and 64.4%. Under the assumption that the share of transferred knowledge depends on the number of co-inventors, the share of transferred knowledge was between 13.41% and 47.8%. These figures clearly suggest that the discontinuation of inventors leads to considerable losses of knowledge in the respective RIS, even if it is assumed that the inventor's knowledge is completely transferred to all co-inventors during the cooperation.

Table 1. Share of knowledge of the previous period that remains in the network.

Region		1997–1999	2000–2002	2003–2005	2006–2008	Average
Aachen	I	76.4	66.2	43.1	66.1	63.0
	II	37.2	34.1	31.0	45.3	36.9
	III	28.0	24.8	26.9	29.4	27.3
Dresden	I	92.7	68.6	73.2	88.4	80.7
	II	50.4	48.4	55.4	64.4	54.6
	III	32.3	40.8	45.6	47.8	41.6
Halle	I	72.1	37.4	27.9	30.1	41.9
	II	29.6	20.0	18.9	24.1	23.2
	III	23.9	20.0	19.1	20.0	20.7
Jena	I	90.8	59.6	73.8	81.2	76.4
	II	43.6	38.5	44.5	55.6	45.5
	III	25.0	30.0	27.2	37.6	30.0
Karlsruhe	I	57.6	60.4	51.9	68.8	59.7
	II	26.6	32.6	39.0	48.4	36.7
	III	13.4	22.4	30.1	35.7	25.4
Kassel	I	56.4	43.2	47.7	74.0	55.3
	II	24.9	22.9	29.1	45.2	30.5
	III	16.7	16.4	16.2	21.7	17.7
Magdeburg	I	48.8	47.2	44.4	41.1	45.4
	II	25.9	24.2	26.1	27.1	25.8
	III	18.0	15.7	16.2	16.0	16.5
Rostock	I	69.1	34.8	48.5	68.6	55.3
	II	27.2	25.2	36.9	44.6	33.5
	III	17.2	24.6	27.4	24.1	23.3
Siegen	I	65.4	55.4	60.2	74.9	64.0
	II	34.8	35.1	41.9	50.1	40.5
	III	23.8	26.7	30.0	30.3	27.7
All regions	I	66.5	62.9	57.8	71.7	64.7
	II	34.8	35.7	39.7	47.9	39.5
	III	23.5	25.9	28.0	31.7	27.3
Average values	I	69.9	52.5	52.3	65.9	60.15
	II	33.3	31.2	35.9	45.0	36.4
	III	22.0	24.6	26.5	29.2	25.6

Notes: The values in the first row are based in the assumption that the knowledge of an inventor is completely passed on to all his co-inventors. For the values in the second row it is assumed that only 50% of an inventor's knowledge is transferred to co-inventors. The third row contains the values based on the assumption that the knowledge of a patent is equally divided between all co-inventors.

5. What Determines the Persistence of Knowledge in Regional Networks?

The previous sections showed that inventor networks are characterized by diverging shares of persistent knowledge. This raises the question of how far micro-level fluidity and a network's macro structure are related to the share of knowledge that is passed on to other members during their cooperation (knowledge persistence). To test for such effects, we estimated the fixed-effect models with different independent variables such as the share of reoccurring inventors from t-1, the share of discontinued inventors from t-1, and measures for the network structure (Table 2). Due to the relatively low number of observations and the considerable correlation between many of the measures for network characteristics, only one independent variable was included in a model. Since this method may imply an omitted variable bias, the results should be regarded with caution.

Table 2. Inventor fluidity, network characteristics, and the share of knowledge transfer over time.

	I	II	III	IV	V	VI	VII	VIII	IX
				Knowledge Persistence—Complete Transfer					
Share of discontinued inventors t-1	−2.175 *** (0.361)	-	-	-	-	-	-	-	-
Share of new inventors t-0	-	−1.211 * (0.830)	-	-	-	-	-	-	-
Average team size t-1	-	-	0.3849 *** (0.0723)	-	-	-	-	-	-
Share of isolates t-1	-	-	-	−3.016 *** (1.131)	-	-	-	-	-
Average component size t-1	-	-	-	-	0.220 *** (0.060)	-	-	-	-
Share of the largest component t-1	-	-	-	-	-	1.267 ** (0.541)	-	-	-
Number of inventors in largest component t-1	-	-	-	-	-	-	0.0003 *** (0.0002)	-	-
Mean degree t-1	-	-	-	-	-	-	-	0.0316 (0.0387)	-
Density t-1	-	-	-	-	-	-	-	-	−1.264 (1.097)
Constant	−0.0289 (0.114)	1.476 *** (0.488)	−0.3139 * (0.1711)	0.961 *** (0.157)	−0.129 (0.208)	0.472 *** (0.092)	0.559 *** (0.0825)	0.453 ** (0.191)	0.569 *** (0.0648)
Adjusted R^2	0.864	0.624	0.7956	0.698	0.760	0.676	0.639	0.5872	0.5938
				Knowledge Persistence—50% Transfer					
	I	II	III	IV	V	VI	VII	VIII	IX
Share of discontinued inventors t-1	−0.606 *** (0.136)	-	-	-	-	-	-	-	-
Share of new inventors t-0	-	−0.606 * (0.321)	-	-	-	-	-	-	-
Average team size t-1	-	-	0.1924 *** (0.0362)	-	-	-	-	-	-
Share of isolates t-1	-	-	-	−1.508 *** (0.566)	-	-	-	-	-
Average component size t-1	-	-	-	-	0.110 *** (0.0300)	-	-	-	-
Share of the largest component t-1	-	-	-	-	-	0.634 ** (0.270)	-	-	-
Number of inventors in largest component t-1	-	-	-	-	-	-	0.00002 *** (0.0000)	-	-
Mean degree t-1	-	-	-	-	-	-	-	0.0173 (0.0205)	-
Density t-1	-	-	-	-	-	-	-	-	−0.407 (0.631)
Constant	0.581 *** (0.071)	0.738 *** (0.244)	−0.1570 * (0.0856)	0.480 *** (0.078)	−0.0647 (0.104)	0.236 *** (0.046)	0.280 *** (0.0413)	0.347 *** (0.101)	0.406 *** (0.0373)
Adjusted R^2	0.802	0.624	0.7956	0.698	0.760	0.676	0.639	0.7189	0.6811
				Knowledge Persistence—Weighted Transfer					
	I	II	III	IV	V	VI	VII	VIII	IX
Share of discontinued inventors t-1	−0.386 *** (0.0915)	-	-	-	-	-	-	-	-
Share of new inventors t-0	-	−0.575 *** (0.202)	-	-	-	-	-	-	-
Average team size t-1	-	-	0.1380 *** (0.0228)	-	-	-	-	-	-
Share of isolates t-1	-	-	-	−1.010 *** (0.365)	-	-	-	-	-
Average component size t-1	-	-	-	-	0.0754 *** (0.0187)	-	-	-	-
Share of the largest component t-1	-	-	-	-	-	0.376 ** (0.181)	-	-	-
Number of inventors in largest component t-1	-	-	-	-	-	-	0.0001 * (0.0000)	-	-
Mean degree t-1	-	-	-	-	-	-	-	0.00841 (0.00910)	-
Density t-1	-	-	-	-	-	-	-	-	0.447 (0.415)
Constant	0.348 *** (0.0475)	−0.591 *** (0.154)	−0.1576 *** (0.0534)	0.289 *** (0.0506)	−0.0817 (0.0649)	0.130 *** (0.0308)	0.155 *** (0.0269)	0.253 *** (0.0448)	0.275 *** (0.0245)
Adjusted R^2	0.775	0.615	0.7911	0.683	0.764	0.633	0.614	0.8971	0.7490

Notes: Fixed-effects panel regressions. Robust standard errors in parentheses. *** Statistically significant at the 1% level; ** Statistically significant at the 5% level; * Statistically significant at the 10% level. The number of observations was 36 in all models (nine regions).

As expected, we found a highly significant negative relationship between the share of discontinued inventors of the previous period (t-1), the share of new inventors, and the share of persistent knowledge of a network (Table 2, Models I and II). We used several measures for the size of a network and its components. The average team size measures the number of inventors who cooperate in a project and may directly exchange their knowledge.

The average component size and the number of inventors in the largest component represent the inventors who are directly and indirectly connected by co-inventorship. The share of inventors in the largest component as well as the share of isolates represent the level of (non-)integration of inventors in a RIS. The results indicate that larger inventor teams (Hypothesis 1) as well as larger network's components enhance the share of persistent knowledge (Hypothesis 2).

The positive relationship between the share of inventors in the largest component and the measure for knowledge persistence as well as the negative relationship between knowledge persistence and the share of isolates suggests that knowledge persistence is higher in well-integrated networks (Hypothesis 2). However, relationships based on other measures of network cohesion such as mean degree (Model VIII) or density (Model XI) or even using different types of clustering coefficients were found to be statistically insignificant. This result contradicts our Hypothesis 3. All in all, the results clearly suggest that the continuity of inventors, larger teams and components, and a high level of integration of inventors may be important for keeping the knowledge of discontinued inventors available.

6. The Effect of Knowledge Persistence on Network Performance

To investigate the effect of persistent knowledge and new knowledge on the performance of the respective RIS, we used patent productivity as a measure of performance. Patent productivity is defined as the number of patents filed by private sector innovators with at least one inventor residing in the respective region per 1000 R&D employees. While this metric reflects the level of the efficiency of RIS (Fritsch 2002; Fritsch and Slavtchev 2011), we also used the percentage change of patent productivity to analyze the development of that level. An advantage of this second performance measure is that relating indicators for the dynamics of the composition and the structure of networks to changes of patent productivity may lead to a more robust identification of causal relationships.

All models include the share of manufacturing employees in establishments with less than 50 employees as a control variable. This variable accounts for the observation that the number of patents per unit of R&D input tends to be higher in smaller firms than in larger firms (for a theoretical explanation and discussion, see Cohen and Klepper 1996). Hence, we expect a negative sign for the estimated coefficient of this variable. In the models for the change of patent productivity, we also included the level of patent productivity in the previous period. The estimated coefficient of this variable should have a negative sign for two reasons. First, regions with an already relatively high level of patent productivity may have lower potentials for improvements than regions that are characterized by a comparatively low performance. Second, the level of patent productivity in the base year controls for a regression to the mean effect. This effect denotes the phenomenon that periods with relatively large changes in one direction may be followed by periods where the changes are relatively small, or even work in the opposite direction.

The estimation results presented in Table 3 provide empirical evidence for the positive connection between the performance of a network and the two potential sources of knowledge, namely new and persistent knowledge. Thus, we found a significantly positive relationship between a network's patent productivity and the share of new inventors (Model I) as well as with the share of persistent knowledge (Models III and IV). The non-significance of the share of persistent knowledge in Model II that does not include the share of new knowledge may be caused by the relatively high correlation between the measures of these two knowledge sources (see Table A5 in the Appendix A). The share of persistent knowledge has, however, only a weakly significant effect if the change in patent productivity is taken as the dependent variable (Models VII and VIII). The insignificance of the coefficient of the weighted measure of knowledge transfer in Models V and IX may result from the fact that the construction of this measure is based on the assumption that only smaller amounts of the total knowledge are transferred, so that the share of persistent knowledge is, perhaps, underestimated.

Table 3. The relation between the share of persistent knowledge, the share of new inventors, and patent productivity.

	Patent Productivity (ln)						Change of Patent Productivity (%)					
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
Share of new inventors	2.714 *** (0.892)	-	3.044 *** (0.874)	3.044 *** (0.874)	3.239 *** (0.940)	2.290 ** (0.930)	-	-	-	2.345 *** (0.861)	2.345 *** (0.861)	2.676 *** (0.925)
Share of persistent knowledge												
– complete transfer	-	0.293 (0.323)	0.494 * (0.275)	-	-	-	0.610 * (0.316)	-	-	0.631 ** (0.281)		
– 50% transfer	-	-	-	0.988 * (0.549)	-	-	-	1.219 * (0.633)	-		1.262 ** (0.562)	
– weighted transfer	-	-	-	-	1.370 (0.920)	-	-	-	0.890 (1.018)			1.548 * (0.919)
Employment share of manufacturing establishments <50 employees	0.518 (0.717)	2.498 *** (0.839)	1.988 *** (0.713)	1.988 *** (0.713)	1.978 *** (0.753)	0.950 (0.766)	1.946 ** (0.783)	1.946 ** (0.783)	1.840 ** (0.859)	1.816 *** (0.697)	1.816 *** (0.697)	1.874 ** (0.751)
Patent productivity in t-1 (ln)	-	-	-	-	-	−0.911 *** (0.177)	−0.517 *** (0.186)	−0.517 *** (0.186)	−0.614 *** (0.192)	−0.684 *** (0.176)	−0.684 *** (0.176)	−0.758 *** (0.175)
Constant	−2.721 *** (0.639)	−1.130 *** (0.365)	−3.403 *** (0.720)	−3.403 *** (0.720)	−3.484 *** (0.807)	−2.366 *** (0.742)	−1.031 *** (0.319)	−1.031 *** (0.319)	−0.824 ** (0.338)	−2.820 *** (0.715)	−2.820 *** (0.715)	−2.992 *** (0.806)
Adjusted R^2	0.6615	0.551	0.5858	0.6183	0.6901	0.5347	0.495	0.495	0.435	0.7017	0.7017	0.5858

Notes: Fixed-effects panel regressions. Robust standard errors in parentheses. *** Statistically significant at the 1 % level; ** Statistically significant at the 5% level; * Statistically significant at the 10% level. The number of observations was 36 in all models (nine regions).

We also found statistically positive relationships for our measure of new knowledge in the models for the change in patent productivity (Models VI–XII). For two out of our three measures of knowledge persistence, we also found a statistically significant relationship with the expected positive sign (Table 3, Models VII–IX). Again, the weighted knowledge transfer remained statistically insignificant in models that did not include the share of new inventors (Model IX). When we introduced the share of new inventors (Models X–XII), all three measures of knowledge persistence were statistically significant, supporting our earlier finding that both existing and new knowledge are extremely important to the process of enhancing the efficiency of a RIS.

All in all, these results indicate that the generation of inventions may benefit from both persistent knowledge and new sources of knowledge. This is consistent with our Hypotheses 4 and 5. The effect of our measure for new knowledge—the share of new inventors—is, however, considerably more robust at higher levels of statistical significance. This pattern suggests that new knowledge may be more important for the performance of RIS than old knowledge. We can, however, not exclude that the reason for the poor performance of our measure of persistent knowledge is due to its construction. If the interpretation is correct, that new knowledge is more important for the performance of a RIS than older knowledge, which could also contribute to explaining the rather high levels of inventor fluidity in the networks under investigation. New ideas are mainly introduced by new people, and inventors switch their cooperation partners because they believe that this may be more promising for producing newness than continuing to cooperate with their old partners or their former collaborators.

We have argued that new inventors who enter the network as part of a component create new opportunities of knowledge recombination by making their knowledge available to co-inventors (Section 2). Hence, they should have a stronger effect on the performance of a RIS than inventors who enter as an isolate. In order to test this assertion, we distinguished between new inventors who entered as part of a component and those who entered as isolates. Consistent with our expectations, we found that only those new inventors who were attached to a component had a significantly positive effect on the performance of the respective RIS (Models I, II, V, and VI of Table 4). This result may also be regarded as confirmation of the findings of Wuchty et al. (2007) and Jones et al. (2008) that team inventions are of higher quality than inventions by single inventors.

Table 4. The relationship between the share of persistent knowledge and patent productivity.

	Patent Productivity (ln)				Change of Patent Productivity (%)			
	I	II	III	IV	V	VI	VII	VIII
Share of new inventors attached to components	0.681 *** (0.224)	-	-	-	0.595 ** (0.241)	-	-	-
Share of new inventors that are isolates	-	0.703 (2.265)	-	-	-	0.260 (2.128)	-	-
Share of new inventors attached to components with at least one old inventor	-	-	−2.954 *** (1.033)	-	-	-	−2.448 ** (0.971)	-
Share of new inventors attached to a completely new component	-	-	-	2.323 ** (0.988)	-	-	-	1.992 ** (0.912)
Employment share of manufacturing establishments <50 employees	−0.831 (1.151)	1.941 ** (0.897)	0.690 (0.804)	1.529 ** (0.704)	−0.461 (1.099)	1.526 * (0.901)	0.485 (0.843)	1.048 (0.782)
Patent productivity in t-1 (ln)	-	-	-	-	−0.886 *** (0.177)	−0.691 *** (0.181)	−0.717 *** (0.158)	−0.674 *** (0.161)
Constant	−0.394 (0.240)	−0.831 *** (0.235)	0.370 (0.469)	−2.312 *** (0.648)	−0.419 * (0.249)	−0.627 ** (0.266)	0.356 (0.456)	−1.866 *** (0.613)
Adjusted R^2	0.6611	0.5380	0.6505	0.6202	0.5352	0.4175	0.5392	0.5137

Notes: Fixed-effects panel regressions. Robust standard errors in parentheses. *** Statistically significant at the 1 % level; ** Statistically significant at the 5% level; * Statistically significant at the 10% level. The number of observations was 36 in all models (nine regions). To sum up, our results indicate that it is the new knowledge of new people that drives the performance of RIS. The share of old knowledge that remains in a regional inventor network across subsequent time periods is of only minor importance.

In a final step of analysis, we compared the effects of new inventors who were attached to a component with at least one continuing inventor with new inventors who entered as part of a component that did not include any continuing inventor. The idea behind this approach is that combinations of old and new knowledge may be particularly important for the performance of the respective RIS. Hence, one might expect that new inventors who enter as part of a component that also includes a continuing inventor have a stronger effect on RIS performance. The results of Models III, IV, VII, and VIII in Table 4 clearly suggest the opposite (i.e., components that entirely consist of new inventors have a strong effect on RIS, while the effect of those newcomers who are attached to a component that also comprises at least one old inventor remains completely insignificant). This result underlines our findings of the relative effect of old and new knowledge (Table 3). It is new inventors who emerge as new components that drive the performance of RIS. In contrast, combinations of new knowledge and the knowledge of continuing inventors seem to be unimportant.

7. Discussion and Conclusions

If inventors are no longer active in innovation networks, their knowledge for the respective RIS may be lost. Assuming that inventors transfer at least parts of their knowledge during their cooperation with other inventors, we constructed indicators for the persistence of discontinuing inventors' knowledge. Based on these measures, we found that the discontinuation of inventors can lead to large losses of knowledge, and that the share of these losses varies quite considerably across regions and time periods.

Using our measures for the persistence of knowledge, we analyzed the role of network characteristics in knowledge persistence. We found a positive relationship between the share of transferred knowledge and measures that indicate the connectedness of network members. According to our expectations, more knowledge is transferred and preserved over time in more densely connected network structures. We also found a positive relationship between knowledge persistence and the size of a network's components. Hence, the size of the components of a network and dense relationships among inventors are positively related with the persistence of knowledge across time.

In a next step, we estimated the effect of the share of persistent knowledge that is transferred between two subsequent time periods and the share of new knowledge that is introduced by new inventors on the performance of the respective RIS. RIS performance was measured by patent productivity and the change in patent productivity. The results of these analyses indicate that both old and new knowledge may make a positive contribution to RIS performance, but that the effect of new knowledge, measured by the share of new inventors, is considerably more important. Moreover, we found that only newcomers who were attached to a component that entirely consisted of new inventors had a positive effect on the performance of the respective RIS. New inventors who were attached to a component with old inventors as well as new inventors who entered as isolates had no significant effect.

In a nutshell, the knowledge of discontinuing inventors may particularly remain in large and dense networks. Hence, one important way by which networks contribute to the performance of RIS is to make knowledge of discontinuing inventors available in later time periods. Both new and persistent old knowledge contribute to the performance of RIS, but the effect of new knowledge is much stronger. The significant role played by new actors and their knowledge in the generation of inventions may also explain why inventor teams are rather unstable. A main implication of our analysis is that the ability of regions to attract knowledgeable actors from outside can make an important contribution to local innovation and economic prosperity.

Our analysis is not without limitations. Since patents cover only a part of total innovation activities in a region, our method of estimating the share of persistent knowledge could lead to an underestimation of that knowledge. For example, a patent-based analysis neglects inventions that cannot be patented (incremental inventions and results of basic research) as well as inventions that, for various reasons, are not filed for patenting (Hall et al. 2014; Walter et al. 2011). Moreover, inventors may exchange knowledge in many other, often rather, informal ways. A further limitation of our empirical analysis is the relatively low number of observations (regions and time periods).

Further analyses should try to overcome these shortcomings by including other channels of knowledge transfer (see Fritsch et al. 2020) and by generating datasets with larger numbers of observations. In particular, further work in this field should test different indicators for knowledge persistence as well as for the performance of RIS.

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Appendix A

Table A1. Numbers of nodes, ties, components, and total patents in different time periods.

	Aachen				*Dresden*			
	Number of				**Number of**			
	Inventors	**Ties**	**Components**	**Patents**	**Inventors**	**Ties**	**Components**	**Patents**
94-96	2219	5480	407	1858	1948	6298	362	1458
97-99	2799	7202	482	2455	2791	10,798	400	2556
00-02	3643	13,944	141	2866	3121	13,274	421	2295
03-05	3283	13,208	546	1873	3306	14,578	416	2062
06-08	3135	11,840	506	1900	3707	17,430	446	2522

Table A1. *Cont.*

	Halle				*Jena*			
	Number of				**Number of**			
	Inventors	**Ties**	**Components**	**Patents**	**Inventors**	**Ties**	**Components**	**Patents**
94-96	815	3082	128	485	1153	3722	200	753
97-99	1183	4392	199	941	1789	7212	259	1477
00-02	1230	5664	209	615	1917	8922	244	1147
03-05	842	3172	164	384	1925	9004	254	1089
06-08	642	2164	141	320	1936	8438	290	1152
	Karlsruhe				*Kassel*			
	Number of				**Number of**			
	Inventors	**Ties**	**Components**	**Patents**	**Inventors**	**Ties**	**Components**	**Patents**
94-96	1339	3544	290	2313	739	1838	159	509
97-99	2745	10,256	475	4327	1118	3212	238	740
00-02	4849	22,520	688	3932	1107	3354	260	677
03-05	4657	22,212	649	3073	1115	3860	221	726
06-08	4972	23,420	622	3924	1326	4332	254	828
	Magdeburg				*Rostock*			
	Number of				**Number of**			
	Inventors	**Ties**	**Components**	**Patents**	**Inventors**	**Ties**	**Components**	**Patents**
94-96	635	1710	143	414	243	514	59	178
97-99	865	2406	178	513	426	1342	75	411
00-02	1008	3504	208	577	412	1592	68	235
03-05	977	3048	206	526	371	1568	56	188
06-08	909	2880	196	518	466	1842	78	256
	Siegen				*All regions*			
	Number of				**Number of**			
	Inventors	**Ties**	**Components**	**Patents**	**Inventors**	**Ties**	**Components**	**Patents**
94-96	754	1776	152	662	9845	27,964	1900	8630
97-99	1051	3024	192	820	14,767	49,844	2498	14,240
00-02	1095	3698	200	759	15,394	63,856	2439	13,103
03-05	1007	3482	188	742	17,483	74,132	2700	10,663
06-08	1231	4586	194	928	18,324	76,932	2727	12,348

Table A2. Shares of discontinued inventors and new inventors in the case study regions in different time periods.

	Share of Discontinued Inventors	**Share of New Inventors**	**Share of Discontinued Inventors**	**Share of New Inventors**
	Aachen		Kassel	
1997–1999	0.7388	0.7388	0.8391	0.8399
2000–2002	0.7383	0.7736	0.8024	0.8464
2003–2005	0.6902	0.7548	0.7819	0.8502
2006–2008	0.6571	0.7544	0.7692	0.8363
	Dresden		Magdeburg	
1997–1999	0.7715	0.7101	0.8399	0.8428
2000–2002	0.6885	0.6405	0.8335	0.8621
2003–2005	0.6326	0.6071	0.7990	0.8628
2006–2008	0.6078	0.5967	0.7869	0.8680

Table A2. *Cont.*

	Share of Discontinued Inventors	Share of New Inventors	Share of Discontinued Inventors	Share of New Inventors
	Halle		Rostock	
1997–1999	0.7903	0.7870	0.8416	0.8357
2000–2002	0.8016	0.8163	0.7372	0.7670
2003–2005	0.7672	0.8230	0.6873	0.7547
2006–2008	0.7274	0.8193	0.7082	0.7940
	Jena		Siegen	
1997–1999	0.7732	0.7719	0.7821	0.7821
2000–2002	0.6978	0.7366	0.7023	0.7543
2003–2005	0.7049	0.7787	0.6594	0.7319
2006–2008	0.6226	0.7004	0.6442	0.7474
	Karlsruhe			
1997–1999	0.8984	0.8984		
2000–2002	0.7862	0.8125		
2003–2005	0.7078	0.7505		
2006–2008	0.6378	0.7200		

Table A3. Descriptive statistics.

	Mean	Median	Minimum	Maximum	Standard Deviation
Share of persistent knowledge	0.504	0.471	0.201	0.884	0.175
Share of discontinued inventors	0.740	0.739	0.608	0.898	0.072
Share of new inventors	0.777	0.776	0.597	0.898	0.070
Share of re-emerging inventors	0.260	0.261	0.102	0.392	0.072
Share of isolates	0.087	0.084	0.033	0.188	0.037
Share of the largest component	0.098	0.072	0.023	0.333	0.079
Average component size	4.102	3.936	2.774	6.073	0.975
Mean degree	5.355	5.565	3.225	7.260	1.165
Patent productivity (ln)	−0.368	−0.416	−0.785	0.547	0.259
Change in patent productivity (ln)	−0.038	−0.048	−0.486	0.337	0.188
Employment share of manufacturing establishments <50 employees	0.350	0.331	0.187	0.560	0.106
Share of service employment	0.877	0.876	0.758	0.971	0.048
Number of links	6785	3860	514	23,420	5982
Average team size	2.711	2.790	2.002	3.324	0.320

Table A4. Number of co-patents, single patents, mean degree (all regions).

	94–96	97–99	00–02	03–05	06–08	94–08
Total number of patents	8.63	14.24	13.10	10.66	12.35	58.98
Number of co-patents	7.37	12.60	11.85	9.50	11.14	52.46
Share of co-patents in %	85.45	88.46	90.42	89.07	90.20	88.93
Number of patents with single inventor	1.26	1.64	1.26	1.17	1.21	6.53
Number of inventors per patent	2.71	2.82	2.99	3.07	3.00	2.91
Number of inventors per co-patents	3.40	3.51	3.65	3.70	3.58	3.58
Mean degree	3.76	5.11	5.51	5.44	5.36	3.76
Average path lengths	2.22	3.57	3.85	3.77	3.83	3.45

Table A5. Correlation of variables.

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1	Share of persistent knowledge	1.00												
2	Share of discontinued inventors	−0.66 ***	1.00											
3	Share of new inventors	−0.66 ***	0.84 ***	1.00										
4	Share of re-emerging inventors	0.66 ***	−1.00	−0.84 ***	1.00									
5	Share of isolates	−0.33	0.45 ***	0.40	−0.45 ***	1.00								
6	Share of the largest component	0.58 ***	−0.54 ***	−0.64 ***	0.54 ***	−0.34	1.00							
7	Average component size	0.55 ***	−61 ***	−0.64 ***	0.61 ***	−0.89 ***	0.62 ***	1.00						
8	Mean degree	0.45 ***	−0.36	−0.48 ***	0.36	−0.61 ***	0.54 ***	0.79 ***	1.00					
9	Patent productivity (ln)	0.32	0.11	−0.24	−0.11	0.21	0.24	0.02	0.31	1.00				
10	Change in patent productivity (ln)	0.26	0.03	0.03	−0.03	−0.01	−0.18	−0.07	0.06	0.29	1.00			
11	Employment share of manufacturing establishments <50 employees	−0.29	0.23	0.06	−0.23	−0.08	0.07	0.02	0.01	−0.29	0.06	1.00		
12	Number of inventors	0.51 ***	−0.17	−0.51 ***	0.37	−0.44 ***	0.33	0.60 ***	0.53 ***	0.46 ***	−0.12	−0.54 ***	1.00	
13	Number of ties	0.50 ***	−0.42 ***	−0.3 ***	0.42 ***	−0.55 ***	0.38 ***	0.70	0.61 ***	0.40 ***	−0.14	−0.49 ***	0.98 ***	1.00
14	Average team size	0.24	−0.46 ***	−0.36	0.46 ***	−0.81 ***	0.38	0.77 ***	0.63	−0.38	−0.06	0.27	−0.18	0.20

Notes: Spearman rank correlation coefficients. *** Statistically significant at the 1% level The number of observations was 45 and 36, respectively (nine regions).

Notes

1 Another issue with identifying cooperative relationships between organizations is that some members of such organizations may file patent applications as private inventors. This is a particularly relevant scenario in Germany, because the professor's privilege that allowed university researchers to file inventions for patenting on their own account was only abolished in 2002, while our period of analysis was 1994–2008. Moreover, even after this regulatory change, university professors are still entitled to patent as private inventors if their university is not interested in the exploitation of their invention (Von Proff et al. 2012). One main reason why universities may not use their right to patent an invention is that they do not want to pay the patent fees. The share of such cases is quite significant, but can considerably differ between universities and time periods.

2 If we assume that knowledge remains in the network if the respective applicant is still present in the successive period, then the share of persistent knowledge varies between 0.0% and 84% (average value 55.5%).

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economies

Article

Website Premia for Extensive Margins of International Firm Activities: Evidence for SMEs from 34 Countries †

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† The data from the Flash Euromarometer 421 can be downloaded free of charge after registration at http://www.gesis/eurobarometer. Stata code used to generate the empirical results reported in this note is available from the author.

Abstract: This paper uses firm-level data from the Flash Eurobarometer 421 survey conducted in June 2015 in 34 European countries to investigate the link between having a website and international firm activities in small- and medium-sized enterprises (SMEs). We find that firms that are present on the web more often export, import, engage in research and development cooperation with international partners, work as subcontractors for firms from other countries, use firms in other countries as subcontractors, and perform foreign direct investments—both inside and outside the European Union. The estimated website premia are statistically highly significant after controlling for firm size, country, and sector of economic activity. Furthermore, the size of these premia can be considered to be large. Internationally active firms tend to have a website.

Keywords: website premia; international firm activities; Flash Eurobarometer 421

JEL Classification: D22; F14; F23; L25

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1. Motivation

Presence on the web is today considered as an important part of a firm's strategy to successfully make a living. This tends to be even more important in times of the COVID-19 pandemic, when quarantines and lockdowns increase the costs of face-to-face contact with (potential) buyers and sellers. Wagner (2021) uses firm-level data from the World Bank Enterprise surveys conducted in 2019 and from the COVID-19 follow-up surveys conducted in 2020 in ten European countries to investigate the link between having a website before the pandemic and firm survival until 2020. The estimated positive effect of web presence is statistically highly significant ceteris paribus after controlling for various firm characteristics that are known to be related to firm survival. Furthermore, the size of this estimated effect can be considered to be large on average. Similarly, Muzi et al. (2022) report, based on firm-level data collected for 34 economies up to 18 months into the COVID-19 crisis, that businesses that have a website are more likely to continue existing. A website helps firms to survive.

Furthermore, Wagner (2022) shows that, in 2019, firms from 18 European countries that had a website were larger, older, more productive, and more often exporters, product innovators, process innovators, and (partly) foreign-owned firms than firms without a website. Good firms tend to have a website.

Given this high importance of a web presence for the performance of firms, it comes as a surprise that there seems to be no comprehensive evidence on the existence of websites in firms with various forms of international activities.[1] This note contributes to the literature by reporting descriptive evidence on the share of firms with a website in 34 European countries in 2015 based on the Flash Eurobarometer 421 surveys conducted among small- and medium-sized enterprises in these countries. We look at differences between firms with and without a website in the use of various types of international activities using estimates of so-called website premia that show the percentage difference between firms with and without a website, controlling for firm size, country of origin, and sector of economic activity of the firm.

We expect these website premia to be positive for international activities for two reasons.

First, having a website reduces information costs for potential business partners in other countries. Potential importers and customers in other countries can more easily see details of the products or services provided. Producers in foreign countries can more easily see which products or services a firm in another country that is a potential importer of their products or services might be interested in. A match of partners in cooperative agreements on research and development projects is more easily initiated, and the same holds for agreements in subcontracting (as principal or agent).

Second, from results reported in Wagner (2022) for firms from 18 European countries (based on data from different surveys conducted in 2019), we know that older, more productive, and innovative firms tend to have a website—and these firm characteristics are known to be positively related to international firm activities.

To anticipate the most important result, we find that firms that are present on the web are more active internationally—they more often export, import, engage in research and development cooperation with international partners, work as subcontractors for firms from other countries, use firms in other countries as subcontractors, and perform foreign direct investments—both inside and outside the European Union. The estimated website premia are statistically highly significant after controlling for firm size, country of origin, and sector of economic activity. Furthermore, the size of these premia can be considered to be large. The take-home message, therefore, is that internationally active firms tend to have a website.

The rest of the paper is organized as follows. Section 2 introduces the data used and discusses the international firm activities that are looked at. Section 3 reports results from the econometric investigation. Section 4 concludes.

2. Data and Discussion of Variables

The firm-level data used in this study are taken from the Flash Eurobarometer 421 survey conducted in June 2015 in 34 European countries.[2] All firms are small- and medium-sized enterprises (SMEs) with 1 to 249 employees.

In the survey, firms were asked in question Q11_1, "Is it possible to look at a website presenting your products and/or services?" Firms that answered "yes" are classified as firms with a web presence.

Descriptive evidence on the share of firms with a web presence in the total sample and by country is reported in Table 1. While the overall share of firms with a website in the sample is 75.75 percent, figures differ widely between the 34 countries. Web presence is only 49.00 percent in Albania and 49.64 percent in Bulgaria, while 88.98 percent of all firms in the sample have a website in Sweden and 92.59 percent in Denmark.

At the bottom of Table 1, the share of firms with a website is reported by sector of (main) economic activity of the firm. While firms from manufacturing and services are more often present on the web compared to the overall average figure, and firms from retail and industry have a lower rate of web presence, the figures do not differ by order of magnitude.

In the empirical investigation of the link between web presence and various types of international firm activities, firm size is controlled for. Firm size is measured as the number of employees (in full-time equivalents) at the time of the survey; see question D1a.

In the empirical study, we look at various types of international firm activities inside and beyond the European Union.

We consider exports, imports, working with a partner based abroad for research and development (R&D) purposes, working as a subcontractor for a company based abroad, using a subcontractor for a company based abroad, and investing in a company based abroad. If a firm stated in the survey that it did one of these activities in the last three years (in question q2 with regard to countries inside the European Union or in question q3 with regard to countries outside the European Union), it is considered as an exporter to the EU, etc. Each firm, therefore, can be active or not in 12 different types of international activities.

In questions Q6 and Q10, firms were asked to which countries they exported in 2014, or which countries they did import from, respectively. The answers were coded in a way that allowed the computation of the number of destinations exported to or imported from between zero and nine (see the questionnaire for details).

Furthermore, firms are divided by broad sectors of activity (manufacturing, retail, services, and industry) based on information in variable nace_b.

Descriptive statistics for all variables are reported for the whole sample used in the empirical investigation in Appendix A, Table A1.

Table 1. Share of SMEs with web presence, 2015.

Country/Sector	Number of Firms	Share of Firms with Website (Percent)
All	13,710	75.75
Albania	100	49.00
Austria	476	87.61
Belgium	487	82.14
Bulgaria	421	49.64
Croatia	481	79.21
Cyprus	193	67.88
Czech Republic	474	86.71
Denmark	486	92.59
Estonia	466	65.45
Finland	486	85.39
France	468	70.09
Germany	467	83.51
Greece	486	81.07
Hungary	468	78.21
Iceland	184	76.09
Ireland	471	76.43
Italy	466	63.30
Latvia	479	69.52
Lithuania	480	67.08
Luxemburg	194	72.68
Makedonia	169	51.48
Malta	197	72.08
Moldavia	191	62.30
Montenegro	194	77.32
Netherlands	468	85.47
Poland	444	73.87
Portugal	479	67.85
Romania	480	55.42
Slovak Republic	495	82.83
Spain	486	75.10
Sweden	490	88.98
Turkey	473	82.03
United Kingdom	440	80.45
Manufacturing (NACE C)	2982	80.05
Retail (NACE G)	4216	73.53
Services (NACE H,I,J,K,L,M,N)	4007	78.36
Industry (NACE B,D,E,F)	2505	70.22

Source: Own calculation based on Flash Eurobarometer 421; see text for details.

3. Testing for Website Premia in International Firm Activities

To test for the difference in the types of international firm activities listed in Section 2 between firms with and without a website, and to document the size of these differences, an empirical approach is applied that modifies a standard approach used in hundreds of empirical investigations on the differences between exporters and non-exporters that has been introduced by Bernard and Jensen (1995, 1999). Studies of this type use data for firms to compute so-called exporter premia, defined as the ceteris paribus percentage difference in a firm characteristic—e.g., labor productivity—between exporters and non-exporters. These premia are computed from a regression of log labor productivity on the current export status dummy and a set of control variables:

$$\ln LP_i = a + ß \text{ Export}_i + c \text{ Control}_i + e_t \tag{1}$$

where i is the index of the firm, LP is labor productivity, Export is a dummy variable for current export status (1 if the firm exports, 0 else), Control is a vector of control variables, and e is an error term. The exporter premium, computed from the estimated coefficient ß as 100(exp(ß) − 1), shows the average percentage difference between exporters and non-exporters controlling for the characteristics included in the vector Control (see Wagner (2007) for a more complete exposition of this method).

Here, we look at differences between firms with and without a website (instead of differences between exporters and non-exporters) and are interested in the existence and size of website premia instead of exporter premia (see Wagner 2022). For international firm activities that are measured by dummy variables (the 12 extensive margins listed in Section 2), the empirical model is estimated by Probit instead. Therefore, (1) becomes (2)

$$\text{Indicator}_i = a + ß \text{ Website}_i + c \text{ Control}_i + e_{it} \tag{2}$$

where i is the index of the firm, Indicator is a dummy variable for the use of a form of international firm activity, Website is a dummy variable for the presence of a website in the firm (1 if the firm has a website, 0 else), Control is a vector of control variables (that consists of a measure of firm size, and dummy variables for countries and sectors of economic activity), and e is an error term. The website premium is computed as the estimated average marginal effects of the website dummy variable.

For the number of markets in exports or imports, (1) becomes (3)

$$\ln \text{number}_i = a + ß \text{ Website}_i + c \text{ Control}_i + e_{it} \tag{3}$$

where i is the index of the firm, number is the log of the number of markets in exports or imports, Website is a dummy variable for the presence of a website in the firm (1 if the firm has a website, 0 else), Control is a vector of control variables (that consists of a measure of firm size, and dummy variables for countries and sectors of economic activity), and e is an error term. Note that due to the log transformation, only firms that export to or import from at least one destination are included in the computations.

The website premium, computed from the estimated coefficient ß as 100(exp(ß) − 1), shows the average percentage difference between firms with and without a website, controlling for firm size, country of origin of the firm, and the broad economic sector that it is active in.

Results are reported in Table 2. The broader picture that is shown is perfectly clear: firms that are present on the web are more often active in international economic activities. The estimated website premia are statistically highly significant ceteris paribus after controlling for firm size, country, and sector of economic activity. Furthermore, the size of these premia can be considered to be large.

Table 2. Website premia (percent) for margins of international firm activities.

Variable	Premia	Prob-Value
Export to EU countries	14.35	0.000
Import from EU counties	16.41	0.000
R&D cooperation within EU	4.92	0.000
Subcontractor (agent) within EU	4.58	0.000
Subcontractor (principal) within EU	6.92	0.000
Foreign direct investor within EU	0.48	0.000
Export to Non-EU countries	0.31	0.000
Import from Non-EU countries	11.52	0.000
R&D cooperation beyond EU	3.23	0.000
Subcontractor (agent) beyond EU	3.75	0.000
Subcontractor (principal) beyond EU	4.15	0.000
Foreign direct investor beyond EU	1.51	0.000
Number of export markets	20.17	0.000
Number of import markets	10.25	0.000

Source: Own calculations with data from Flash Eurobarometer 421. The website premium shows the average percentage difference between firms with and without a website, controlling for firm size, country of origin of the firm, and the broad economic sector it is active in; for details, see text.

However, it is an open question (that is asked in the same way when exporter premia are discussed) whether these premia are due to the self-selection of more internationally active firms into web presence or whether these premia are the effect of having a website.

4. Concluding Remarks

This paper demonstrates that having a website is positively related to international firm activities. Website premia are large for all types of international firm activities looked at here. Does this study imply that in order to be active in international markets, firms should have a website, or that having a website will help the firms to be internationally active? This is an open question (that is asked in the same way when exporter premia are discussed) because we do not know whether these premia are due to the self-selection of internationally active firms into web presence, or whether they are the effect of having a website. This cannot be investigated with the data at hand. To answer this important question, longitudinal data for firms are needed that cover several years and that include a sufficiently large number of firms that switch their status between having a website and not over time (in both directions). To the best of my knowledge, such data are not available as of today. Let us collect it!

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Appendix A

Table A1. Descriptive statistics for sample (N = 13,710) used in estimations.

Variable	Mean	Std. Dev.
Web presence	0.758	0.43
(Dummy; 1 = yes)		
Firm size	31.88	44.02
(Number of employees)		

Table A1. *Cont.*

Variable	Mean	Std. Dev.
Export to EU countries	0.395	0.49
(Dummy; 1 = yes)		
Import from EU countries	0.492	0.50
(Dummy; 1 = yes)		
R&D cooperation within EU	0.100	0.30
(Dummy; 1 = yes)		
Subcontractor (agent) within EU	0.158	0.36
(Dummy; 1 = yes)		
Subcontractor (principal) within EU	0.185	0.39
(Dummy; 1 = yes)		
Foreign direct investor within EU	0.045	0.21
(Dummy; 1 = yes)		
Export to Non-EU countries	0.262	0.44
(Dummy; 1 = yes)		
Import from Non-EU countries	0.277	0.45
(Dummy; 1 = yes)		
R&D cooperation beyond EU	0.051	0.22
(Dummy; 1 = yes)		
Subcontractor (agent) beyond EU	0.072	0.26
(Dummy; 1 = yes)		
Subcontractor (principal) beyond EU	0.091	0.29
(Dummy; 1 = yes)		
Foreign direct investor beyond EU	0.030	0.17
(Dummy; 1 = yes)		
Number of export markets	0.860	1.43
Number of import markets	0.867	1.17

Source: Own calculations with data from Flash Eurobarometer 421; for details, see text.

Notes

1 See Gopalan et al. (2022) for website presence and simultaneously exporting and importing, Huang and Song (2019) for internet use and exports in China, Li et al. (2022) for internet use and firms' exports and imports in China.

2 See Table 1 for a list of the countries covered in the survey. Data are available free of charge after registration from http://www.gesis/eurobarometer (accessed on 1 September 2022).

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