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An Empirical Examination of the Incremental Contribution of Stock Characteristics in UK Stock Returns

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Abstract: This study uses the Bayesian approach to examine the incremental contribution of stock characteristics to the investment opportunity set in U.K. stock returns. The paper finds that size, book-to-market (BM) ratio, and momentum characteristics all make a significant incremental contribution to the investment opportunity set when there is unrestricted short selling. However, no short selling constraints eliminate the incremental contribution of the size and BM characteristics, but not the momentum characteristic. The use of additional stock characteristics such as stock issues, accruals, profitability, and asset growth leads to a significant incremental contribution beyond the size, BM, and momentum characteristics when there is unrestricted short selling, but no short selling constraints largely eliminates the incremental contribution of the additional characteristics.

Keywords: stock characteristics; investment opportunity set; no short selling

1. Introduction

There is a long history that stock characteristics have a significant predictive ability of cross-sectional expected excess stock returns. The three most prominent characteristics have been size (Banz 1981), book-to-market (BM) ratio (Fama and French 1992), and momentum (Jegadeesh and Titman 1993). There has been debate in the empirical literature as to whether these predictive patterns can be explained by different measures of systematic risk from linear factor models such as Daniel and Titman (1997), and Davis, Fama and French (Davis et al. 2000). A recent study by Chordia, Goyal and Shanken (Chordia et al. 2015) examine the relative contributions of both betas and stock characteristics in explaining the cross-sectional variation in expected excess returns. Chordia et al. find that stock characteristics make the dominant contribution to explaining cross-sectional variation in expected excess returns.

During the past two decades, a number of studies have identified additional stock characteristics that predict cross-sectional stock returns. A partial list includes stock issues (Pontiff and Woodgate 2008), accruals (Sloan 1996), profitability (Novy-Marx 2013), asset growth (Titman et al. 2004), and idiosyncratic volatility (Ang et al. 2006) among others[1]. Harvey, Liu and Zhu (Harvey et al. 2016) document 314 variables that prior research has found to predict stock returns (Green et al. 2017).

Much of the empirical evidence of stock characteristics comes from spreads in portfolio returns from one or two dimensional portfolio sorts on the basis of stock characteristics or from large *t*-statistics in the Fama and MacBeth (1973) cross-sectional regressions. However, this evidence does not address

[1] Excellent surveys of the role of stock characteristics in cross-sectional stock returns include Subrahmanyam (2010); Cochrane (2011); Goyal (2012); and Nagel (2013).

the marginal impact that additional stock characteristics have on expected return spreads in the presence of other characteristics. Fama and French (2006) examine this issue by forming portfolios on the basis of expected return estimates from the Fama and MacBeth cross-sectional regressions and compare the impact on average return spreads when adding additional stock characteristics to the Fama and MacBeth regressions. Fama and French find that there is only a marginal increase in average return spreads with additional characteristics, even where these characteristics have large Fama and MacBeth t-statistics. Fama and French (2015) extend this analysis and explore why additional stock characteristics only have a minor impact on expected return spreads even when they have large statistical significance in the Fama and MacBeth cross-sectional regressions. Lewellen (2015) finds that there is only a modest increase in average return spreads across decile portfolios in moving from a model with the size, BM, and momentum characteristics, to one with seven characteristics, or fifteen characteristics.

Fama and French (2015) examine the incremental contribution of stock characteristics on the investment opportunity set. They focus on the size, BM, and momentum characteristics. Fama and French use the Gibbons, Ross and Shanken (Gibbons et al. 1989) test of mean-variance efficiency to examine if quintile portfolios formed by expected excess returns estimates from the Fama and MacBeth (1973) regressions using only two stock characteristics lies on the mean-variance frontier of an augmented investment universe that also includes quintile portfolios formed by expected excess returns estimates using all three characteristics. They find that all three characteristics make a significant incremental contribution to the investment opportunity set. However, the optimal tangency portfolios require large short positions and so the higher Sharpe (1966) performance is not attainable by investors. Imposing no short selling constraints, Fama and French find that the incremental contribution of all three characteristics in terms of higher Sharpe performance disappears. The finding that no short selling constraints often hurts the mean-variance performance of trading strategies is consistent with De Roon, Nijman and Werker (De Roon et al. 2001), Li, Sarkar and Wang (Li et al. 2003), and Briere and Szafarz (2017a, 2017b) among others.

Considering the role of no short selling constraints on the performance of trading strategies is important as a lot of investors are unable to short sell and even when can short sell, short selling can be costly (Fama and French 2015). Bris, Goetzmann and Zhu (Bris et al. 2007) find short selling is allowed in 35 out of 47 countries. Even in markets which allow short selling, temporary bans on short selling can be imposed such as in the UK, where short selling was banned in financial stocks between late 2008 and early 2009. Since 2012, the EU short selling regulation has banned naked short selling and investors must report net short positions above a certain limit. Briere and Szafarz (2017a) point out that finding a stock lender can be costly and the investor can be exposed to a liquidity shortage (Jones and Lamont 2002). Managed funds such as open-end mutual funds often face legal restrictions on short selling[2]. European mutual funds subject to UCITS cannot take physical short positions and can only borrow up to 10% of net assets. Best and Grauer (1991, 1992) argue that portfolio constraints like no short selling will almost always be binding as unconstrained mean-variance efficient frontiers often have no all positive weight portfolios.

This paper examines the incremental contribution of stock characteristics on the investment opportunity set in UK stock returns in the presence of no short selling constraints following a similar approach to Fama and French (2015). I evaluate the incremental contribution in terms of higher Sharpe (1966) performance of adding quintile portfolios formed using expected excess returns from a larger model of characteristics to the investment universe of quintile portfolios formed using expected excess returns from a smaller model of stock characteristics. I consider the case where unrestricted short selling is allowed and where no short selling is allowed in the risky assets. I use the Bayesian

[2] Almazan, Brown, Carlson, and Chapman (Almazan et al. 2004) find that only a tiny fraction of U.S. mutual funds engage in short selling.

approach of Wang (1998) to estimate the benefits of higher Sharpe performance and evaluate statistical significance. I use the first two models of stock characteristics of Lewellen (2015). The first model includes the size, BM, and momentum characteristics and the second model adds stock issues, accruals, profitability, and asset growth characteristics.

My study makes three contributions to the literature. First, I complement and extend the recent studies of Fama and French (2006, 2015) and Lewellen (2015) by examining the incremental contribution of stock characteristics in a different market and formally testing the incremental contribution of stock characteristics in the presence of no short selling constraints. Recent studies by Harvey (2017) and Hou, Xue and Zhang (Hou et al. 2017) highlight the importance of replication in Finance, which is common in other fields of science. Second, I extend the prior literature on the role of stock characteristics in UK stock returns such as Levis (1989), Strong and Xu (1997), Dissanaike (1999), Gregory, Harris and Michou (Gregory et al. 2001), Hon and Tonks (2003), Morelli (2007), and Qing and Turner (2014) among others[3]. I extend this literature by considering the incremental contribution of stock characteristics on the investment opportunity set in UK stock returns and examining the impact of no short selling constraints on the incremental contribution. Third, I complement and extend the evidence that examines the impact of no short selling constraints on the mean-variance performance of trading strategies such as De Roon et al. (2001), Li et al. (2003), Ehling and Ramos (2006), Eun, Huang and Lai (Eun et al. 2008), and Briere and Szafarz (2017a, 2017b) among others. I extend this literature by looking at the impact of no short selling constraints on the incremental contribution of stock characteristics.

There are four main findings in my study. First, all of the stock characteristics have a significant predictive ability of future monthly excess returns in the Fama and MacBeth (1973) cross-sectional regressions, with the exception of the accruals characteristic. Second, I find that all of the model 1 characteristics make a significant incremental contribution to the investment opportunity set when investors are allowed unrestricted short selling. However, the optimal portfolios do require large short positions. Third, imposing no short selling restrictions substantially reduces the incremental contribution of the momentum characteristic and eliminates the incremental contribution of the size and BM characteristics. Fourth, I find that the additional model 2 characteristics make a significant incremental contribution to the investment opportunity set when there is unrestricted short selling. No short selling constraints eliminate the incremental contribution of the stock issues, accruals, and asset growth characteristics, but not profitability. My results suggest that there is little to be gained in moving beyond the model 1 characteristics for a characteristic-based model of stock returns.

My study is organized as follows. Section 2 presents the research method. Section 3 describes the data used in the study. Section 4 reports the empirical results and the final section concludes.

2. Research Method

I examine the impact of stock characteristics on the investment opportunity set following a similar approach to Fama and French (2015). I consider the impact of adding quintile portfolios sorted by expected excess returns from a model using a larger group of stock characteristics to a benchmark investment universe of quintile portfolios sorted by expected excess returns using a smaller group of stock characteristics. I then formally test whether there is a significant shift in the investment opportunity set from adding the quintile portfolios to the benchmark investment universe to see if the additional stock characteristics make a significant incremental contribution to the investment opportunity set.

The expected excess returns of each stock are estimated each month using the Fama and MacBeth (1973) cross-sectional regression approach. Define M as the number of stock characteristics in a given

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3 Qing and Turner (2014) present a novel study which examines the impact of stock characteristics in the London market between 1825 and 1870.

model. For each month of the sample period (t = 1, . . . ,T), the following cross-sectional regression is run:

$$r_{it} = \gamma_{0t} + \Sigma_{m=1}{}^{M}\gamma_{mt}z_{mt-1} + u_{it} \quad (1)$$

where r_{it} is the excess return on asset i at time t, z_{mt-1} is the value of the mth stock characteristic of asset i at time t−1, and u_{it} is a random error term of asset i at time t. The Fama and MacBeth cross-sectional regression assumes a linear functional form between the excess returns and stock characteristics. It is possible that nonlinearities are important in the releations between stock characteristics and excess returns. Kirby (2015) and Freyberger, Neuhier and Weber (Freyberger et al. 2017) provide different approaches to examine this issue. The expected excess returns are given by:

$$E(r_{it}) = \gamma_0 + \Sigma_{m=1}{}^{M}\gamma_m z_{mt-1} \quad (2)$$

where γ_0 and γ_m are the time-series averages of the monthly γ_{0t} and γ_{mt} coefficients. Each month during the sample period, all stocks are ranked on the basis of their $E(r_{it})$ and grouped into quintile portfolios as in Fama and French (2015). I then calculate the value weighted portfolio excess returns for each quintile portfolio. Where a security has missing return data during the month due to temporary suspension or death, I code the missing returns to zero as in Liu and Strong (2008). I correct for the delisting bias of Shumway (1997) by assigning a −100% return if the death is deemed valueless[4] as in Dimson, Nagel and Quigley (Dimson et al. 2003).

Estimating expected excess returns using the Fama and MacBeth (1973) cross-sectional regression approach is used in a number of recent studies such as Fama and French (2006, 2015), Lewellen (2015), and Clarke (2016) among others. Using the full sample estimates of γ_0 and γ_m implies that investors cannot implement these as portfolio strategies. As a result, my study focuses on in-sample performance rather than out-of-sample performance. Fama and French point out that using full sample slopes has much greater precision compared to using rolling window estimates. Likewise if the portfolios are formed using monthly γ_{0t} and γ_{mt} coefficients, then most of the spread in portfolio returns will be due to unexpected returns and not due to expected return patterns. Lewellen examines the predictive ability of expected excess returns using the Fama and MacBeth approach.

Fama and French (2015) use the Gibbons et al. (1989) test of mean-variance efficiency to examine the impact of adding quintile portfolios formed by expected excess returns using three stock characteristics to an investment universe of quintile portfolios formed by expected excess returns using two stock characteristics. The two groups of quintile portfolios are defined as the augmented investment universe. If the third characteristic has no incremental impact on the investment opportunity set, then the optimal tangency portfolio of the benchmark investment universe will be the same as the optimal tangency portfolio of the augmented investment universe. This analysis can be generalized to any two models of stock characteristics. The Gibbons et al. test does not accommodate short selling restrictions. Tests of mean-variance efficiency in the presence of no short sales constraints have been developed by Basak, Jagannathan and Sun (Basak et al. 2002)[5].

An alternative approach to testing mean-variance efficiency in the presence of short selling constraints is the Bayesian approach of Wang (1998)[6] and Li et al. (2003). This approach was developed when no risk-free asset exists but the same approach can be modified to the case where there is risk-free lending and borrowing. I use the Bayesian approach to examine the portfolio efficiency of the optimal

4 Using the death event information on the London Share Price Database (LSPD) provided by London Business School.

5 A number of studies examine whether there is mean-variance spanning between two mean-variance frontiers when there is no risk-free asset. De Roon and Nijman (2001) and Kan and Zhou (2012) provide excellent reviews of alternative tests of mean-variance spanning when unrestricted short selling is allowed. De Roon et al. (2001) develop the corresponding tests of mean-variance spanning when there are no short selling constraints and transaction costs.

6 Recent applications of the Bayesian approach include Hodrick and Zhang (2014) and Liu (2016) in tests of the benefits of international diversification.

portfolios in the augmented investment universe relative to the optimal portfolios in the benchmark investment universe to capture the incremental contribution of the additional stock characteristics.

Li et al. (2003) argue that the Bayesian approach has a number of advantages over the asymptotic tests of De Roon et al. (2001). First, the Bayesian approach incorporates the uncertainty of finite samples into the posterior distribution. Second, the Bayesian approach is easier to implement and can use a range of different performance measures. Third, we get the exact inference of the magnitude of diversification benefits. Fourth, under no short selling constraints the asymptotic tests rely on a first-order linear approximation[7] but the Bayesian approach uses the exact nonlinear function of u and V.

I measure the incremental contribution of an additional individual (or group of) stock characteristics as the increase in Sharpe (1966) performance from adding the quintile portfolios formed by expected excess returns using the extended model of stock characteristics to the benchmark investment universe. Define N as the number of risky assets in the benchmark universe and 2N as the number of risky assets in the augmented investment universe, x is the (2N, 1) vector of optimal weights in the augmented investment univegrse, and x_b is the (2N, 1) vector of optimal weights in the benchmark investment universe, where the first N cells are zero and the remaining N cells are the optimal weights of the N risky assets in the benchmark investment universe.

The performance measure is given by:

$$\text{DSharpe} = \theta^* - \theta_b \tag{3}$$

where $\theta^* = x'u/(x'Vx)^{1/2}$,$\theta_b = x_b'u/(x_b'Vx_b)^{1/2}$, u is a (2N, 1) vector of expected excess returns, and V is a (2N, 2N) covariance matrix. The DSharpe measure captures the increase in Sharpe performance in adding the quintile portfolios formed using expected excess returns from the extended model of stock characteristics to the benchmark investment universe. If the additional stock characteristics make no incremental contribution to the investment opportunity set, then DSharpe = 0. I estimate the DSharpe measures for the case where unrestricted short selling is allowed and for the case where no short selling is allowed in the risky assets. When the risk-free asset exists, all optimal portfolios (which are combinations of the risk-free asset and the tangency portfolio) have the same Sharpe performance. As a result, the DSharpe measure can be estimated using any optimal portfolio on the corresponding mean-variance frontiers of the benchmark and augmented investment universes. I estimate the optimal portfolios using a given value of risk aversion, which I set equal to 3 as in Tu and Zhou (2011).

To examine the statistical significance of the DSharpe measure, the Bayesian approach of Wang (1998) assumes that the 2N asset excess returns have a multivariate normal distribution[8]. I assume a non-informative prior for the expected excess returns u and covariance matrix V. Define u_s and V_s as the sample moments of the expected excess returns and covariance matrix, and r as the (T, 2N) matrix of excess returns of the risky assets. The posterior probability density function is given by:

$$p(u, V \mid R) = p(u \mid V, u_s, T) \bullet p(V \mid V_s, T) \tag{4}$$

where $p(u \mid V, u_s, T)$ is the conditional distribution of a multivariate normal $(u_s, (1/T)V)$ distribution and $p(V \mid V_s, T)$ is the marginal posterior distribution that has an inverse Wishart $(TV, T-1)$ distribution (Zellner 1971).

Wang (1998) proposes a Monte Carlo method to approximate the posterior distribution. I use the following approach. First, a random V matrix is drawn from an inverse Wishart $(TV_s, T-1)$

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7 Basak et al. (2002) point out using a linear function may lead to a large approximation error when no short selling constraints are imposed. Basak et al find that the standard error of their mean-variance inefficiency measure increases when no short selling constraints are imposed, which is the opposite of Wang (1998) and Li et al. (2003).

8 We can view the normality assumption as a working approximation to monthly excess returns. A non-parametric test along the lines of Ledoit and Wolf (2008) could address this issue in future research.

distribution. Second, a random u vector is drawn from a multivariate normal (u_s, (1/T)V) distribution. Third, given the u and V from steps 1 and 2, the DSharpe measure is estimated from Equation (3)[9]. Fourth, steps 1 to 3 are repeated 1000 times as in Hodrick and Zhang (2014) to generate the approximate posterior distribution of the DSharpe measure.

The posterior distribution of the DSharpe measure is then used to assess the magnitude of the incremental contribution of the additional stock characteristics to the investment opportunity set and provide a test of statistical significance. The average value of the posterior distribution of the DSharpe measure provides the average increase in Sharpe performance in adding the quintile portfolios formed using expected excess returns with the extended model of stock characteristics to the benchmark investment universe. I use the 5% percentile value of the DSharpe measure to assess the statistical significance of whether the average DSharpe measure = 0 (Hodrick and Zhang 2014). If the 5% percentile value of the DSharpe measure exceeds zero, I reject the null hypothesis that the additional stock characteristics make no incremental contribution to the investment opportunity set.

3. Data

My sample includes all UK stocks between July 1983 and December 2015. I exclude investment trusts[10], secondary shares, and foreign companies. I use the first two models of security characteristics of Lewellen (2015). The first model includes size, BM, and momentum characteristics. The second model includes stock issues, accruals, profitability, and asset growth characteristics[11]. The market values and stock returns data are collected from LSPD. The accounting data is collected from Worldscope provided by Thomson Financial. I use the return on the one-month Treasury Bill as the risk-free asset (collected from LSPD and Datastream).

The characteristics involving only accounting data can only be calculated once a year. I assume that the monthly characteristic data, using only accounting data, between July of year t to June of year t + 1 are equal to the annual characteristic values calculated during year t − 1. This approach assumes that the accounting data from the fiscal year-end of the previous calendar year t − 1 would be known to investors by the start of July in year t. All of the characteristic data is winsorized at the 1% and 99% levels as in Lewellen (2015). The characteristics are defined as follows:

3.1. Size

The size of the company is given by the monthly market values. I use the log of the monthly market values at the prior month-end to measure size. I set companies with zero market values to missing values.

3.2. Book-to-Market (BM) Ratio

The monthly BM ratio is calculated using the book value of equity at the fiscal year-end (WC03501) during the previous calendar year divided by the prior month-end market value. I set companies with negative book values or zero market values to missing values. I use the log of the BM ratio in my analysis.

3.3. Momentum

I calculate the momentum characteristic each month as the prior cumulative returns of the stock between months −12 to −2. Companies must have continuous return observations during the past 12 months, otherwise the momentum characteristic is set to missing values.

9 If the optimal portfolios lie on the inefficient side of the mean-variance frontier, I set the corresponding Sharpe performance to zero.
10 Investment trusts are equivalent to U.S. closed-end funds.
11 Fama and French (2008) examine the same group of characteristics in their study in U.S. stock returns.

3.4. Stock Issues

I calculate the stock issues characteristic as in Lewellen (2015). I use the log growth in split-adjusted shares from month −36 to month −1. I require companies to have the relevant data in both months −36 and −1, otherwise set to missing values.

3.5. Accruals

I calculate the annual accruals similar to Fama and French (2008) as the change in operating working capital per split-adjusted shares from years $t-2$ to $t-1$ divided by book equity per split-adjusted share at year $t-1$. I require companies to have the relevant data in years $t-2$ and $t-1$ and have a positive book value per share at year $t-1$, otherwise set to missing values. Operating working capital is defined as current assets (WC02201) minus cash and short-term investments (WC02001) minus current liabilities (WC03101) plus debt in current liabilities (WC03051). I use the book value per share to measure book equity (WC05476).

3.6. Profitability

I use the gross profitability measure as in Novy-Marx (2013) and Sun, Wie and Xie (Sun et al. 2014) defined as sales (WC01001) minus cost of goods sold (WC01051) divided by total assets (WC02999).

3.7. Asset Growth

I calculate asset growth similar to Fama and French (2008) as the log of the ratio of assets per split-adjusted shares in year $t-1$ to year $t-2$. I calculate the assets per split-adjusted share using total assets (WC02999) and common shares outstanding (WC05301).

Table 1 reports summary statistics of the monthly excess returns and stock characteristics across the July 1983 and December 2015 period. The table includes the time-series averages of the cross-sectional mean and standard deviation of the monthly excess returns (%) and the stock characteristic values at the start of each month. N is the time-series average of the number of stocks with the relevant data each month.

Table 1. Summary Statistics.

Characteristics	Mean	Standard Deviation	N
Excess return	0.687	18.109	1647
Size	10.508	2.075	1832
BM	−0.659	1.098	1292
Momentum	0.130	0.507	1422
Stock issues	0.253	0.511	1325
Accruals	0.010	0.762	1158
Profitability	0.354	0.282	1261
Asset growth	0.031	0.408	1394

The table reports summary statistics of the stock characteristics and excess returns for the individual stocks between July 1983 and December 2015. The summary statistics include the time-series averages of the cross-sectional mean, and standard deviation of the characteristic values at the start of each month and the monthly excess returns (%). N is the time-series average of the number of securities with characteristic values for that month.

Table 1 shows that the average mean excess return is 0.687% with a large cross-sectional volatility of 18.109%. Lewellen (2015) also reports a large cross-sectional volatility in individual stocks in U.S. stock returns. The average number of companies with characteristic data across the sample period varies across characteristics from 1158 (accruals) and 1832 (size).

4. Empirical Results

I begin my empirical analysis by examining the predictive ability of the stock characteristics of the monthly excess returns using the Fama and MacBeth (1973) cross-sectional regressions. I run the regressions using the stock characteristics individually, then using the model 1 characteristics jointly, and then using all the model 2 characteristics. Table 2 reports the cross-sectional regression results. The table includes the time-series average slope coefficients (spreads) for each characteristic and the corresponding Fama and MacBeth *t*-statistic. The R^2 column is the time-series average of the adjusted R^2 from the monthly cross-sectional regressions.

Table 2. Fama and MacBeth (1973) Cross-Sectional Regressions.

Panel A: Individual	Slope	*t*-Statistic	R^2
Size	−0.185	−4.09 [1]	0.007
BM	0.231	3.56 [1]	0.007
Momentum	0.888	4.28 [1]	0.009
Stock issues	−0.462	−3.72 [1]	0.004
Accruals	−0.120	−1.46	0.002
Profitability	0.672	3.76 [1]	0.003
Asset growth	−0.849	−5.66 [1]	0.004
Panel B: Model 1	**Slope**	***t*-Statistic**	$\mathbf{R^2}$
Size	−0.138	−3.42 [1]	0.024
BM	0.324	5.84 [1]	
Momentum	1.312	7.06 [1]	
Panel C: Model 2	**Slope**	***t*-Statistic**	$\mathbf{R^2}$
Size	−0.095	−2.37 [1]	0.036
BM	0.394	5.46 [1]	
Momentum	1.306	7.30 [1]	
Stock issues	−0.358	−2.58 [1]	
Accruals	−0.160	−1.19	
Profitability	0.807	5.01 [1]	
Asset growth	−0.699	−3.96 [1]	

[1] Significant at 5%.

The table reports the results of the Fama and MacBeth (1973) cross-sectional regressions of individual excess stock returns on stock characteristics between July 1983 and December 2015. The table includes the time-series average of the monthly slope coefficients on each characteristic and the corresponding Fama and MacBeth *t*-statistic. The R^2 column is the time-series average of the adjusted R^2 from the monthly cross-sectional regressions. Panel A of the table reports the cross-sectional regression results where each characteristic is included individually. Panels B and C report the cross-sectional regressions using the model 1 characteristics and the model 2 characteristics respectively.

Panel A of Table 2 shows that all the stock characteristics, except the accruals characteristic, have a significant predictive ability of monthly excess returns. The signs of the average characteristic spreads are consistent with prior research. The accruals characteristic has the smallest average spread in absolute terms at −0.120%. All of the other stock characteristics have large *t*-statistics from the individual regressions in excess of the cutoff *t*-statistic recommended by Harvey et al. (2016), which controls for multiple testing. The largest average spreads are for asset growth, momentum, and profitability[12] characteristics.

[12] The predictive ability of the profitability characteristic is highly sensitive to the profitability measure used. Using the alternative profitability measures in Fama and French (2008, 2015) and Lewellen (2015), the average spreads can be tiny or even turn significantly negative.

Using the model 1 characteristics in panel B of Table 2, all three characteristics have a significant predictive ability of monthly excess returns with large *t*-statistics. The momentum characteristic has the largest average spread by a long way. There is a sharp increase in the average spread of the momentum characteristic when including the other stock characteristics in the cross-sectional regressions compared to panel A. The Fama and MacBeth (1973) slope coefficients with respect to a given characteristic can be viewed as the excess returns of a zero-cost portfolio that is in long in high values of the characteristic and short in low values of the characteristic controlling for the other characteristics in the regression (Fama 1976). The difference between the average spreads of the momentum characteristic in panels A and B stem from the fact that the zero-cost portfolio in panel B controls for size and BM characteristics.

When using the model 2 characteristics in panel C of Table 2, six out of the seven stock characteristics continue to have significant predictive ability of cross-sectional monthly excess returns. There is a sharp drop in the *t*-statistics for the size and stock issues characteristics, which are now below the cut-off *t*-value of Harvey et al. (2016). The momentum characteristic now has the largest average spread, followed by the profitability and asset growth characteristics.

Table 2 suggests that a number of stock characteristics have large significant average spreads in U.K. stock returns, even when controlling for other characteristics[13]. These findings are in the main similar to Fama and French (2015) and Lewellen (2015) among others in U.S. stock returns. I next examine the incremental contribution of stock characteristics on the investment opportunity set. I begin this analysis using the model 1 characteristics following Fama and French (2015). Each pair of characteristics are used to form the quintile portfolios in the benchmark investment universe and then all three characteristics are used to form the quintile portfolios added to the benchmark investment universe.

Table 3 reports the summary statistics of the posterior distribution of the DSharpe measure for the unconstrained portfolio strategies (panel A) and constrained portfolio strategies (panel B). The summary statistics include the mean, standard deviation, fifth percentile (5%), and the median of the posterior distribution. Panel C reports the sum of the average short positions in the optimal portfolios from the benchmark investment universe and the augmented (Augment) investment universe for the unconstrained portfolio strategies.

Table 3. Posterior Distribution of the DSharpe Measure Using Model 1 Characteristics.

Panel A: Unconstrained	**Mean**	**Standard Deviation**	**5%**	**Median**
Momentum	0.164	0.046	0.090	0.162
BM	0.117	0.039	0.057	0.114
Size	0.059	0.025	0.023	0.056
Panel B: Constrained	**Mean**	**Standard Deviation**	**5%**	**Median**
Momentum	0.090	0.034	0.036	0.089
BM	0.010	0.011	0	0.005
Size	0.019	0.019	0	0.014
Panel C	**Bench**	**Augment**		
Momentum	−2.390	−8.829		
BM	−1.065	−12.863		
Size	−3.017	−5.348		

The table reports the summary statistics of the posterior distribution of the DSharpe measure for the incremental contribution of the model 1 characteristics between July 1983 and December 2015. The summary statistics include the mean, standard deviation, the fifth percentile (5%), and the

13 Kirby (2015) uses the time-series of the monthly spreads as the set of payoffs to evaluate candidate stochastic discount factor models. This approach is used to examine whether the magnitude of the average spreads are consistent with asset pricing models. See also the related study by Back, Nishad and Ostdiek (Back et al. 2015). This approach can be used to examine whether the predictive ability of stock characteristics can be captured by risk factors.

median of the posterior distribution. The model 1 characteristics include size, BM, and momentum. The benchmark (Bench) investment universe consists of excess returns of quintile portfolios formed by expected excess returns using two of the stock characteristics. The augmented (Augment) investment universe adds the excess returns of quintile portfolios formed by expected excess returns using all three characteristics. Panels A and B report the summary statistics of the posterior distribution for the unconstrained portfolio strategies and the constrained portfolio strategies where no short selling is allowed in the risky assets. Panel C reports the sum of the average short positions in the benchmark investment universe and the augmented investment universe. The analysis assumes a risk aversion of 3 in the optimal portfolio strategies.

Panel A of Table 3 shows that for the unconstrained portfolio strategies, all three characteristics make a significant incremental contribution to the investment opportunity set. The mean DSharpe measures for the unconstrained portfolio strategies range between 0.059 (Size) and 0.164 (Momentum). All of the mean DSharpe measures are significant at the 5% percentile. The median DSharpe measures are close to the mean DSharpe measures. The momentum characteristic has the largest increase in Sharpe performance among the three characteristics. These results of the significant incremental contribution of each characteristic to the investment opportunity set, when investors are allowed unrestricted short selling, is similar to Fama and French (2015).

Fama and French (2015) also point out that the higher Sharpe performance will not be attainable for investors if unable to short sell or even where they can short sell, the costs of short selling would eliminate much of the superior performance. The optimal portfolios underlying the increase in Sharpe performance can involve large short positions. Panel C of Table 3 shows that the sum of average short positions can be large, especially in the augmented investment universe. The sum of the average short positions in the augmented investment universes range between −5.348 (Size) and −12.863 (BM). The large short positions are generally concentrated in the low expected excess return portfolios. The results in panel C of Table 3 suggest that the higher Sharpe performance in panel A can only be exploited by large short positions, which is similar to Fama and French (2015).

When the no short selling restrictions are imposed in panel B of Table 3, the significant incremental contribution of the size and BM characteristics to the investment opportunity set disappears. The mean DSharpe measures of the size and BM characteristics are close to zero. There is a drop in the mean DSharpe measure of the momentum characteristic but the mean DSharpe measure remains significant at the 5% percentile. This result suggests that the momentum characteristic is the only characteristic which makes a significant incremental contribution to the investment opportunity set when there are no short selling constraints. Along with the drop in the mean DSharpe measures in panel B, there is also a drop in the volatility of the DSharpe measures. This pattern is similar to Wang (1998) and is due to the lower estimation risk when no short selling constraints are imposed (Frost and Savarino 1988; Jagannathan and Ma 2003). Basak et al. (2002) find that the standard error of their mean-variance inefficiency measure increases in the presence of no short selling constraints, which is different from the Bayesian approach. Basak et al suggest that this result occurs because the linear approximation to a nonlinear function in the asymptotic tests becomes less reliable in the presence of no short selling constraints[14].

The impact of the no short selling constraints on the incremental contribution of stock characteristics is in the main consistent with Fama and French (2015). The difference here is that we find the momentum characteristic continues to have a significant incremental contribution to the investment opportunity set even in the presence of no short selling constraints. The results are also consistent with a number of studies, which show that no short selling hurts the mean-variance performance of trading strategies such as factor investing as Briere and Szafarz (2017a, 2017b). In contrast, Jagannathan and Ma (2003) examining the out-of-sample performance of the global minimum variance (GMV) portfolio

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[14] Li et al. (2003) note a similar problem in the mean-variance spanning test of De Roon et al. (2001).

finds that no short selling constraints improves the performance of the GMV portfolio when using the sample covariance[15] matrix but not for other estimators of the covariance matrix.

I next examine the incremental contribution of the stock issues, accruals, profitability, and asset growth characteristics to the investment opportunity set relative to the model 1 characteristics. The benchmark investment universe is the quintile portfolios formed by expected excess returns using the model 1 characteristics. Each additional characteristic is then used along with the model 1 characteristics to form quintile portfolios to construct the augmented investment universe. I also examine the incremental contribution of all the additional characteristics jointly. Table 4 reports the posterior distribution of the DSharpe measure for the unconstrained portfolio strategies (panel A) and the constrained portfolio strategies (panel B). Panel C reports the sum of the average short positions in the optimal portfolios from the benchmark investment universe and the augmented investment universe for the unconstrained portfolio strategies.

Table 4. Posterior Distribution of the DSharpe Measure of the Additional Model 2 Characteristics.

Panel A: Unconstrained	Mean	Standard Deviation	5%	Median
Stock issues	0.073	0.030	0.029	0.071
Accruals	0.030	0.018	0.007	0.026
Profitability	0.092	0.034	0.041	0.089
Asset Growth	0.063	0.028	0.023	0.061
All	0.151	0.043	0.085	0.149
Panel B: Constrained	**Mean**	**Standard Deviation**	**5%**	**Median**
Stock issues	0.012	0.011	0	0.009
Accruals	0.005	0.007	0	0.002
Profitability	0.031	0.015	0.006	0.030
Asset Growth	0.012	0.010	0	0.010
All	0.051	0.022	0.015	0.051
Panel C	**Bench**	**Augment**		
Stock issues	−2.730	−10.119		
Accruals	−2.722	−4.528		
Profitability	−2.711	−6.753		
Asset Growth	−2.728	−10.565		
All	−2.716	−7.590		

The table reports the summary statistics of the posterior distribution of the DSharpe measure of the incremental contribution of the stock issues, accruals, profitability, and asset growth characteristics between July 1983 and December 2015. The summary statistics include the mean, standard deviation, the fifth percentile (5%), and the median of the posterior distribution. The model 2 characteristics include the model 1 characteristics size, BM, and momentum and the additional characteristics of stock issues, accruals, profitability, and asset growth. The benchmark (Bench) investment universe consists of excess returns of quintile portfolios formed by expected excess returns using the model 1 characteristics. The augmented (Augment) investment universe adds the excess returns of quintile portfolios formed by expected excess returns using the model 1 characteristics and one of the model 2 characteristics or all the model 2 characteristics. Panels A and B report the summary statistics of the posterior distribution for the unconstrained portfolio strategies and the constrained portfolio strategies, where no short selling is allowed in the risky assets. Panel C reports the sum of the average short positions in the benchmark universe and the augmented universe. The analysis assumes a risk aversion of 3 in the optimal portfolio strategies.

Panel A of Table 4 shows that all four additional model 2 characteristics make a significant incremental contribution to the investment opportunity set when there is unrestricted short selling.

[15] This result stems from the fact that no short selling constraints mitigate the impact of estimation risk in covariance matrix estimators with large sampling error such as the sample covariance matrix.

The mean DSharpe measures for the unconstrained portfolio strategies range between 0.030 (Accruals) and 0.092 (Profitability). All of the mean DSharpe measures are significant at the 5% percentile. Using all four characteristics together, there is a significant incremental contribution to the investment opportunity set as reflected in the significant mean DSharpe measure of 0.151.

The optimal portfolios underlying the increase in Sharpe performance in panel A of Table 4 do require large short positions. The sum of the average short positions range between −4.528 (Accruals) and −10.565 (Asset Growth). Imposing no short selling constraints substantially reduces both the mean and volatility of the DSharpe measures in panel B of Table 4 as in Table 3. The significant incremental contribution of the stock issues, accruals, and asset growth characteristics disappears in the presence of no short selling constraints. It is only for the profitability characteristic and using all characteristics together that there is a significant mean DSharpe measure. The incremental contribution of the profitability characteristic is on the borderline of statistical significance.

Table 4 suggests that the incremental contribution of the additional model 2 characteristics considered jointly is marginal in the presence of no short selling constraints. With the exception of the profitability characteristic, none of the individual characteristics make a significant incremental contribution to the investment opportunity set in the presence of no short selling constraints beyond what is contained in the model 1 characteristics. These results on the impact of no short selling constraints on the incremental contribution of stock characteristics are again consistent with Fama and French (2015). Lewellen (2015) also finds that the additional stock characteristics only have a marginal impact on the predictive ability of expected returns beyond the model 1 characteristics.

My analysis so far has formed the quintile portfolios using all stocks. Fama and French (2008) and Lewellen (2015) among others show that stock characteristics often have a stronger predictive ability of cross-sectional stock returns in smaller companies. To examine this issue, I repeat the analysis in Tables 2–4 but this time I only include the largest 350 companies by market value at the start of each month[16]. Tables 5–7 report the corresponding empirical tests.

Table 5. Fama and MacBeth (1973) Cross-Sectional Regressions: Large Stocks.

Panel A: Individual	**Slope**	***t*-Statistic**	**R^2**
Size	−0.013	−0.28	0.014
BM	0.088	1.11	0.019
Momentum	1.381	5.02 [1]	0.033
Stock issues	−0.829	−4.56 [1]	0.010
Accruals	0.042	0.34	0.005
Profitability	0.364	1.75 [2]	0.009
Asset growth	−0.935	−3.97 [1]	0.012
Panel B: Model 1	**Slope**	***t*-Statistic**	**R^2**
Size	0.002	0.049	
BM	0.181	2.84 [1]	0.053
Momentum	1.364	5.38 [1]	
Panel C: Model 2	**Slope**	***t*-Statistic**	**R^2**
Size	−0.025	−0.52	
BM	0.288	3.53 [1]	
Momentum	1.599	6.14 [1]	
Stock issues	−0.660	−3.35 [1]	0.074
Accruals	−0.078	−0.49	
Profitability	0.510	2.62 [1]	
Asset growth	−0.539	−2.00 [1]	

[1] Significant at 5%; [2] Significant at 10%.

[16] Gregory, Tharyan and Christidis (Gregory et al. 2013) use the largest 350 UK stocks to form the factors in the Fama and French (1993) and Carhart (1997) linear factor models.

Table 6. Posterior Distribution of the DSharpe Measure Using Model 1 Characteristics: Large Stocks.

Panel A: Unconstrained	Mean	Standard Deviation	5%	Median
Momentum	0.176	0.048	0.100	0.176
BM	0.071	0.032	0.026	0.067
Size	0.050	0.024	0.017	0.047
Panel B: Constrained	**Mean**	**Standard Deviation**	**5%**	**Median**
Momentum	0.030	0.019	0.001	0.029
BM	0.005	0.007	0	0.002
Size	0.002	0.005	0	0
Panel C	**Bench**	**Augment**		
Momentum	−0.455	−4.918		
BM	−1.918	−7.886		
Size	−2.142	−5.100		

Table 7. Posterior Distribution of the DSharpe Measure of the Additional Model 2 Characteristics: Large Stocks.

Panel A: Unconstrained	Mean	Standard Deviation	5%	Median
Stock issues	0.046	0.024	0.013	0.042
Accruals	0.039	0.021	0.011	0.036
Profitability	0.057	0.028	0.016	0.055
Asset Growth	0.028	0.017	0.007	0.025
All	0.045	0.025	0.012	0.042
Panel B: Constrained	**Mean**	**Standard Deviation**	**5%**	**Median**
Stock issues	0.013	0.010	0	0.012
Accruals	0.006	0.007	0	0.003
Profitability	0.016	0.012	0	0.013
Asset Growth	0.001	0.003	0	0
All	0.017	0.013	0	0.015
Panel C	**Bench**	**Augment**		
Stock issues	−2.344	−5.705		
Accruals	−2.336	−5.378		
Profitability	−2.340	−3.792		
Asset Growth	−2.340	−5.608		
All	−2.342	−4.191		

The table reports the results of the Fama and MacBeth (1973) cross-sectional regressions of individual excess stock returns on stock characteristics between July 1983 and December 2015. The sample only includes the largest 350 stocks by market value at the start of each month. The table includes the time-series average of the monthly slope coefficients on each characteristic and the corresponding Fama and MacBeth *t*-statistic. The R^2 column is the time-series average of the adjusted R^2 from the monthly cross-sectional regressions. Panel A of the table reports the cross-sectional regression results where each characteristic is included individually. Panels B and C report the cross-sectional regressions using the model 1 characteristics and the model 2 characteristics respectively.

The table reports the summary statistics of the posterior distribution of the DSharpe measure of the incremental contribution of the model 1 characteristics between July 1983 and December 2015. The analysis only includes the largest 350 companies by market value each month. The summary statistics include the mean, standard deviation, the fifth percentile (5%), and the median of the posterior distribution. The model 1 characteristics include size, BM, and momentum. The benchmark (Bench) investment universe consists of excess returns of quintile portfolios formed by expected excess returns using two of the stock characteristics. The augmented (Augment) investment universe adds the excess returns of quintile portfolios formed by expected excess returns using all three characteristics. Panels A and B report the summary statistics of the posterior distribution for the unconstrained portfolio strategies and the constrained portfolio strategies where no short selling is allowed in the risky assets. Panel C reports the sum of the average short positions in the benchmark investment universe and the augmented investment universe. The analysis assumes a risk aversion of 3 in the optimal portfolio strategies.

The table reports the summary statistics of the posterior distribution of the DSharpe measure of the incremental contribution of the stock issues, accruals, profitability, and asset growth characteristics between July 1983 and December 2015. The analysis only includes the largest 350 companies by market value each month. The summary statistics include the mean, standard deviation, the fifth percentile (5%), and the median of the posterior distribution. The model 2 characteristics include the model 1 characteristics size, BM, and momentum and the additional characteristics of stock issues, accruals, profitability, and asset growth. The benchmark (Bench) investment universe consists of excess returns of quintile portfolios formed by expected excess returns using the model 1 characteristics. The augmented (Augment) investment universe adds the excess returns of quintile portfolios formed by expected excess returns using the model 1 characteristics and one of the model 2 characteristics or all the model 2 characteristics. Panels A and B report the summary statistics of the posterior distribution for the unconstrained portfolio strategies and the constrained portfolio strategies, where no short selling is allowed in the risky assets. Panel C reports the sum of the average short positions in the benchmark universe and the augmented universe. The analysis assumes a risk aversion of 3 in the optimal portfolio strategies.

Panel A of Table 5 shows that the statistical significance of the average characteristic spreads is weaker for most characteristics in the cross-sectional regressions when only using the largest stocks. It is only momentum, stock issues, profitability, and asset growth characteristics with significant average spreads in the individual cross-sectional regressions at the 10% significance level. The magnitude of the momentum, stock issues, and asset growth spreads are larger than in Table 2, whereas for size, BM, accruals, and profitability characteristics, the spreads are lower when only including the largest stocks.

Using the model 1 characteristics in panel B of Table 5, only the BM and momentum characteristics have significant positive average spreads. The size spread is tiny and is not statistically significant. The magnitude of the BM spread is lower than in Table 2 but the momentum spread remains similar. The patterns in the size and BM spreads are similar to U.S. stock returns in Lewellen (2015) and Fama and French (2015). The pattern in the momentum spread is similar to Lewellen but Fama and French find that the momentum spread is larger in the biggest stocks.

When using all stock characteristics in panel C of Table 5, the BM, momentum, stock issues, profitability, and asset growth characteristics have significant average spreads. The t-statistics on the profitability and asset growth characteristics are below the Harvey et al. (2016) cut-off t-statistic. The magnitude of the average spreads is lower for all the characteristics than in Table 2 except for momentum and stock issues. Most of these patterns are similar to Lewellen (2015) and confirm that a number of stock characteristics have smaller average spreads in the largest stocks.

In panel A of Table 6, all three stock characteristics have a significant incremental contribution to the investment opportunity set in the unconstrained portfolio strategies. The mean DSharpe measures are lower when only including the largest stocks compared to Table 3 for the size and BM characteristics. The mean DSharpe measure for the momentum characteristic is marginally higher in the largest stocks. All of the mean DSharpe measures are significant at the 5% percentile. These patterns are consistent with the difference in the spreads of the model 1 characteristics between the largest stocks and all stocks. The optimal portfolios underlying the increase in Sharpe performance do require large short positions as reflected in the average sum of short positions in panel C of Table 5. The sum of average short positions range between -4.198 (Momentum) and -7.886 (BM). The magnitude of the average short positions is less than observed in Table 3.

Imposing no short selling constraints eliminates the incremental contribution of the size and BM characteristics to the investment opportunity set of the largest stocks in panel B of Table 6. The mean DSharpe measures for the size and BM characteristics are tiny. No short selling constraints substantially reduce the incremental contribution of the momentum characteristic. The mean DSharpe measure of the momentum characteristic is on the borderline of statistical significance. The drop in the mean DSharpe measure of the momentum characteristic is a lot more substantial in the largest stocks compared to Table 3. This result suggests that no short selling constraints has a greater impact on the incremental contribution of stock characteristics to the investment opportunity set among the largest stocks.

When looking at the additional model 2 characteristics in Table 7, all of the characteristics have a significant incremental contribution to the investment opportunity set when only using the largest companies for the unconstrained portfolio strategies. The mean DSharpe measures range between 0.028 (Asset Growth) and 0.046 (Stock Issues). All of the mean DSharpe measures are significant at the 5% percentile. Using all characteristics together has a significant incremental contribution to the investment opportunity set beyond that contained in the model 1 characteristics. The mean DSharpe measures are a lot lower than in Table 4, except for the accruals characteristic. The optimal portfolios underlying the increase in Sharpe performance do require large short positions as reflected in the sum of the average short positions in panel C of Table 7.

Imposing no short selling constraints eliminates the incremental contribution to the investment opportunity set of the additional characteristics individually and jointly, when using the largest stocks. The mean DSharpe measures are tiny and none are significant at the 5% percentile. This pattern is consistent with Table 6 and suggests that no short selling constraints have a bigger impact on the incremental contribution of stock characteristics to the investment opportunity when using the largest stocks. These results are again consistent with the negative impact no short selling constraints has on the mean-variance performance of trading strategies such as De Roon et al. (2001), Li et al. (2003), and Briere and Szafarz (2017a, 2017b) among others.

5. Conclusions

This study uses the Bayesian approach of Wang (1998) to examine the incremental contribution of stock characteristics to the investment opportunity set in UK stock returns. There are four main findings in my study. First, I find that all of the stock characteristics, with the exception of the accruals characteristic, have significant characteristic spreads in the Fama and MacBeth (1973) cross-sectional regressions. The momentum, profitability, and asset growth characteristics have the largest average spreads. A number of the characteristics have *t*-statistics which are larger than the cut-off *t*-statistic of Harvey et al. (2016). The magnitude of the characteristic spreads for the size, BM, accruals, and profitability characteristics are smaller in the largest stocks, whereas the characteristic spreads are larger for momentum and stock issues characteristics. These patterns in characteristic spreads are in the main similar to Fama and French (2015) and Lewellen (2015).

Second, I find that the size, BM, and momentum characteristics all make a significant incremental contribution to the investment opportunity set when investors are allowed unrestricted short selling when only using the model 1 characteristics. This finding is consistent with Fama and French (2015). The momentum characteristic makes the largest incremental contribution among the three model 1 characteristics. The incremental contribution of the size and BM characteristics are smaller when only using the largest stocks. The optimal portfolios underlying the increase in Sharpe performance do require large short positions. This higher performance will not be attainable to investors who face no short selling constraints and even where investors can short sell, the costs of short selling could eliminate much of the superior performance (Fama and French 2015).

Third, I find that imposing no short selling constraints eliminates the incremental contribution of the size and BM characteristics. Only the momentum characteristic makes a significant incremental contribution to the investment opportunity set. This finding is similar to Fama and French (2015) in U.S. stock returns, with the exception that the momentum characteristic has a significant incremental contribution to the investment opportunity set. The mean DSharpe measure on the momentum characteristic is substantially lower in the largest stocks. The impact of no selling constraints is consistent with the impact of no short selling on the mean-variance performance of trading strategies in emerging markets such as De Roon et al. (2001) and Li et al. (2003) and factor investment strategies as Briere and Szafarz (2017a, 2017b).

Fourth, I find that the stock issues, accruals, profitability, and asset growth characteristics all make a significant incremental contribution to the investment opportunity set beyond the model 1 characteristics when there is unrestricted short selling. No short selling constraints eliminate the incremental contribution of the stock issues, accruals, and asset growth characteristics beyond the model 1 characteristics. The profitability characteristic is the only characteristic to make a significant incremental contribution to the investment opportunity set beyond the model 1 characteristics. Using all four characteristics together makes a significant incremental contribution to the investment opportunity set. When only using the largest stocks, none of the additional characteristics either individually or jointly make a significant incremental contribution to the investment opportunity set beyond the model 1 characteristics. This finding is consistent with Lewellen (2015) who finds additional characteristics have only a marginal impact on the predictive power of expected returns beyond the model 1 characteristics.

My results suggest that no short selling constraints substantially reduce or eliminate the incremental contribution of stock characteristics to the investment opportunity set. As a result, there is little to be gained in using additional stock characteristics beyond the model 1 characteristics in forecasting expected excess returns. My analysis does not address whether the predictive power of stock characteristics is due to risk factors or from behavioral reasons. An interesting extension to my study would be to examine if stock characteristics have significant incremental contribution to the investment opportunity set beyond beta models, including factor models where higher moments are important as in Hung, Shackleton and Xu (Hung et al. 2004), linking in with the recent study by Chordia et al. (2015). My examination of the impact of no short selling constraints on the incremental contribution of stock characteristics has taken the extreme cases that the investor can either engage in unrestricted short selling or no short selling. It would be interesting to consider the impact of less stringent short selling constraints on the incremental contribution of stock characteristics to the investment opportunity set as in Briere and Szafarz (2017a) such as 130/30 rule, where there is an upper bound of the total weight of short selling in the risky assets of 0.3. My study has focused on the in-sample performance of the portfolio strategies. It would be of interest to extend the analysis to look at out-of-sample performance along the lines of Lewellen (2015). I leave an examination of these issues to future research.

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