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Empirical Essays on Earnings Forecast Errors and the Risk of Momentum

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1 Introduction

This dissertation examines forecast errors and the risk of equity momentum strategies. There is substantial evidence that analyst forecasts for corporate earnings are overly optimistic, especially long-term forecasts, leading to earnings forecast errors. In Chapter 2, we examine how firm characteristics contribute to this phenomenon. By firm characteristics, we refer to important corporate fundamentals that were identified as significant predictors in the cross-section of stock returns and characteristics that underlie popular risk-factor models, such as the Fama and French five-factor model (Fama & French, 2015) and the q -factor model (Hou, Xue, & Zhang, 2015), which currently serve as benchmarks for explaining variations in cross-sectional stock returns.

This is motivated by studies such as that of Kothari, So, & Verdi (2016), who attribute the accuracy in analysts' forecasts to certain firm characteristics and posit that accuracy generally decreases with uncertainty measures and the forecast horizon. Zhang (2006) examines the role of information uncertainty in short-term stock price continuation anomalies. He defines information uncertainty as "ambiguity with respect to the implications of new information for a firm's value" (Zhang, 2006, p. 105). This ambiguity can potentially stem from two sources: volatility of a firm's underlying fundamentals and poor information. His results suggest that high information uncertainty delays the flow of information into stock prices, which makes especially high-uncertainty stocks vulnerable to behavioural biases (see also Hirshleifer (2001)). We combine these ideas and test in Chapter 2 to what extent important firm characteristics can explain the accuracy in analysts' forecasts in light of uncertainty in these firm characteristics.

We study three investment-based corporate fundamentals, three firm profitability measures, firm size, book-to-market ratio, and portfolio time-series momentum. The focus on investment and profitability measures is based on the findings of Hou, Xue, & Zhang (2017) that investment and profitability, but not liquidity, are the main drivers of the cross-section of

expected returns.

Every year, we assign stocks into 25 portfolios based on their book-to-market ratio and firm size. We find that the earnings forecast errors for small-growth stocks are the largest in magnitude (meaning, the most negative) and have the highest standard errors, by far. We also find that growth stocks carry higher uncertainty in the form of higher standard errors in their investment and profitability measures as well as in monthly excess returns. This provides evidence to the suggestion of Zhang (2006) that high-uncertainty firms are more likely to be growth firms.

Further, we find in panel regressions that measures of corporate investments are negatively related to future earnings forecast errors. This implies that higher investments lead to either lower actual earnings in the next period, higher estimated earnings for the next period or a combination thereof. Higher profitability has the opposite effect and leads to improved future earnings forecast errors. When comparing the results for portfolios of value and growth stocks, we find that the magnitude of the coefficients for the investment and profitability measures is more pronounced for growth stocks. Additionally, the tested corporate fundamentals explain a much higher variance of the earnings forecast errors of growth stocks compared to value stocks.

To our best knowledge, our study in Chapter 2 is the first that directly links the properties of earnings forecast errors to corporate fundamentals underlying the risk factors in the most important cross-sectional models. Moreover, our findings provide further evidence on the role of information uncertainty, potentially caused by the volatility of a firm's underlying fundamentals and poor information, in evaluating a firm's value in light of new information. Secondly, there is substantial evidence that stock market anomalies, in part, reflect forms of mispricing and that stocks share similar components of mispricing (see, e.g., Hirshleifer & Jiang (2010) and Kozak, Nagel, & Santosh (2018)). Stambaugh & Yuan (2017) argue that factor models can be useful to examine whether expected returns reflect some sort of

risk or mispricing. The factors may capture systematic risk, where investors demand a risk premium as compensation for bearing that risk. Or factors can capture sources of mispricing, such as investor sentiment or uncertainty regarding earnings. In Chapter 3, we examine how uncertainty regarding earnings - as measured by earnings forecast errors, which we introduced in Chapter 2 - contribute to the mispricing phenomenon. Earnings forecast errors have been put forward as a mispricing-based explanation of the value premium (Piotroski & So (2012)) and have the advantage of being a non-return-based measure. Therefore, these errors allow for a direct analysis of expectation errors caused by institutional investors and analysts. Studies such as Hou et al. (2017) and Fama & French (2016) demonstrate that popular risk factor models - such as the Fama & French (2015) five-factor model, the Carhart (1997) four-factor model and the Hou et al. (2015) q -factor model - largely summarise the cross-section of average stock returns. Additionally, Hirshleifer & Jiang (2010), Stambaugh & Yuan (2017), and others find that many return-anomaly studies indicate that some form of mispricing is at least partially responsible for the reported anomaly returns. Stambaugh & Yuan (2017) find that their four-factor model with two mispricing factors accommodates a large set of return anomalies even better than the aforementioned four- and five-factor models. In Chapter 3, our study adds to this and tests the extent to which earnings forecast errors as a specific proxy for mispricing are a priced factor when added to well-documented risk-factor models. Using data for the 34 portfolio formation years 1982–2015, we find in time series regressions that, when significant, the coefficient for earnings forecast errors is always strongly positive, which is the case for most of the portfolios carrying larger companies. This implies that less mispricing in the form of less negative earnings forecast errors corresponds to higher contemporaneous returns. Furthermore, adding earnings forecast errors to the factor models lowers the estimated betas of the market excess return and the value risk factor (high minus low, HML) for value stocks in all tested models. Thus, some of the perceived general stock market risk and the value premium for value stocks might instead be uncertainty around

earnings as measured by earnings forecast errors. When added to the Stambaugh & Yuan (2017) four-factor model the coefficient for earnings forecast errors is significant for 18 of the 25 portfolios. Therefore, it is the most significant mispricing factor, by far, among the three included. This indicates that earnings forecasts errors are, on the one hand, related to existing mispricing factors in the literature but, on the other hand, also capture with uncertainty regarding earnings a distinctively different mispricing aspect. Overall, adding earnings forecast errors significantly raises the portion of variability explained in the returns of the 25 size- and book-to-market-sorted portfolios as measured by the adjusted R^2 in all four tested models. This effect is more pronounced for portfolios of large cap and value stocks, where the more complex model including earnings forecast errors is significantly better in explaining portfolio returns as documented in related *F-tests*.

Our contribution to the finance literature in Chapter 3 is threefold. First, to our best knowledge, this is the first study that tests the explanatory power of earnings forecast errors for the cross-section of average portfolio returns in the presence of popular risk factors. Second, the study provides further evidence for the hypothesis that both risk factors and mispricing are significant drivers in the cross-section of stock returns. Third, we reveal that earnings forecasts errors capture with uncertainty around earnings a different dimension of mispricing.

In Chapter 4 of this dissertation, we focus on the risk properties of the momentum factor. Momentum strategies usually buy past winners and sell past losers, which implies a bet on past returns predicting future returns in the cross-section. The academic literature shows that the success of momentum strategies is not limited to U.S. stocks, where it was first identified by Jegadeesh & Titman (1993), but is a widespread phenomenon across major asset classes, regions, and periods. However, investors pay a high price for the strong momentum returns, as they are highly negatively skewed and suffer from infrequent but severe drawdowns: The winners-minus-losers (WML) strategy from Fama and French lost 91.59% within two months

in 1932 and returned -73.43% within three months in 2009 (Barroso & Santa-Clara, 2015, p. 112).

Studies such as those by Barroso & Santa-Clara (2015) and Daniel & Moskowitz (2016) also reveal that the risk of momentum varies substantially over time and is highly predictable. Based on *ex ante* volatility forecasts for momentum a dynamically weighting of the momentum factor WML leads to a doubling of the Sharpe ratio compared to the regular momentum strategy in both studies. Additionally, Barroso & Santa-Clara (2015) find that a dynamic weighting of the momentum factor based on an autoregressive (AR) variance forecast largely eliminates the crash risk of momentum. However, the above-mentioned studies focus almost exclusively on U.S. data. We extend the study of Barroso & Santa-Clara (2015) to a much broader sample and examine whether the predictability of the risk of momentum can be generalised to all developed market equity regions, in other words, the United States, Europe, Japan, and the Asia Pacific ex Japan region. Further, we apply the autoregressive (AR) forecast of Barroso & Santa-Clara (2015) for the variance of momentum to all five Fama and French factors and test whether the predictability of risk is a pervasive phenomenon across all five risk factors.

Here, our contribution to the literature is fivefold. First, we find that the risk of momentum is not only predictable in the United States but generally in all other developed market equity regions, in other words, Europe, Japan, and the Asia Pacific ex Japan region. Second, we reveal that the high autocorrelation of momentum risk is not only limited to the first lag but is statistically significant for up to approximately 10 lags, based on monthly data. Third, we demonstrate that the predictability of the variance is not unique to the momentum strategy but a common characteristic that applies to all five Fama and French factors, i.e. the market excess return (RMRF), size (SMB), value (HML), profitability (RMW), and investments (CMA). Fourth, we find that the risk-managed momentum strategy remains highly successful relative to the regular momentum strategy even after it has been proposed by Barroso &

Santa-Clara (2015). However, we find that the same strategy fails to improve the risk and return measures for the other factors despite the high predictability of their risk. Lastly, when we decompose the risk of momentum, we find that the vast majority of the risk is strategy-specific and is not driven by the variance of the broad stock market. This confirms the results of Barroso & Santa-Clara (2015), and we conclude that this offers a possible explanation for the strong success of the risk-managed strategy of momentum.

The conclusion of this dissertation discusses drawbacks of the results presented here and provides some directions for further research.

2 Earnings Forecast Errors and Firm Characteristics¹

2.1 Chapter Introduction

There is substantial evidence that analyst forecasts for corporate earnings, especially long-term forecasts, are too optimistic, leading to earnings forecast errors. In this paper we examine how firm characteristics contribute to this phenomenon. By firm characteristics, we refer to important corporate fundamentals that were identified as significant predictors in the cross-section of stock returns and characteristics that underlie popular risk-factor models. Our study is motivated by three results from the finance literature. First, several papers, including Kothari et al. (2016), have attributed the accuracy in analysts' forecasts to certain firm characteristics and posit that accuracy generally decreases with uncertainty measures, such as firm complexity and volatility in returns and earnings, and the forecast horizon. Second, since the 1970s, hundreds of firm characteristics have been put forward as being significant predictors in the cross-section of stock returns. However, studies such as that by Green, Hand, & Zhang (2017) have found that only a handful of variables are reliably independent determinants of non-microcap stock returns. Additionally, these variables are mostly unrelated to the characteristics that underlie popular risk-factor models, such as the Fama and French five-factor model (Fama & French, 2015) or the q -factor model (Hou et al., 2015), which currently serve as benchmarks for explaining variation in cross-sectional stock returns. Third, Zhang (2006) has examined the role of information uncertainty in short-term stock price continuation anomalies. He has defined information uncertainty as "ambiguity with respect to the implications of new information for a firm's value" (Zhang, 2006, p. 105). This ambiguity can potentially stem from two sources: volatility of a firm's underlying fundamentals and poor information. His results suggest that high information uncertainty delays the flow of information into stock prices. Thus, the lack of accurate feedback about a

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firm's fundamentals make stocks, especially high-uncertainty stocks, vulnerable to behavioural biases (Hirshleifer, 2001). This study combines these three ideas and tests the extent to which important firm characteristics can explain the accuracy in analysts' forecasts in light of uncertainty in these firm characteristics.

Specifically, we study three investment-based corporate fundamentals, three firm profitability measures, firm size, the book-to-market ratio and portfolio time-series momentum. The three investment-based corporate fundamentals are Investment-to-Assets, Investment Growth and Investment-to-Capital. The three firm profitability measures we use are Operating Profitability, Gross Profitability and Return-on-Equity. The focus on investment and profitability measures is based on the findings of Hou et al. (2017) that investment and profitability, but not liquidity, are the main drivers of the cross-section of expected returns. Thus, we analyse their influence on earnings forecast errors as well.

Every year, we assign stocks into 25 portfolios based on their book-to-market ratio and firm size to draw conclusions about the average earnings forecast errors for these classes of stocks. We find that the earnings forecast errors for small-growth stocks are the largest in magnitude (meaning, the most negative) and have the highest standard errors, by far. This supports the rationale of Zhang (2006), who uses firm size as one proxy of information uncertainty as he argues that small firms are less diversified and have less information available to the market. This poorer information about small firms leads to very negative earnings forecast errors. Additionally, we find that growth stocks carry higher uncertainty in the form of higher standard errors in their investment and profitability measures as well as monthly excess returns. This provides evidence for the suggestion of Zhang (2006) that high-uncertainty firms are more likely to be growth firms.

Using data for the 35 portfolio formation years 1982–2016 we find in panel regressions consistent results across the investment-based measures as well as across the firm profitability measures: Measures of corporate investments are negatively related to future earnings forecast

errors. This implies that higher investments (specifically measured via Investment-to-Capital) lead to either lower actual earnings in the next period, higher estimated earnings for the next period, or a combination thereof. Higher profitability, measured as Operating Profitability and Return-on-Equity, has the opposite effect and leads to improved future earnings forecast errors. The book-to-market ratio also has a significant positive effect on earnings forecast errors, which implies that, *ceteris paribus*, higher valuations (i.e., lower book-to-market ratios) are related to higher estimated future earnings, which manifest in lower (meaning, worse) earnings forecast errors. When separately comparing the results for portfolios of value and growth stocks, the direction for both type of stocks is largely the same. However, the magnitude of the coefficients is more pronounced for growth stocks. Furthermore, the tested corporate fundamentals explain a much higher variance of the earnings forecast errors of growth stocks compared to value stocks.

This study contributes to the finance literature in several ways. First, to our best knowledge, this is the first study that directly links the properties of earnings forecast errors to corporate fundamentals underlying the risk factors in the most important cross-sectional models. Prior studies, such as that by Hughes, Liu, & Su (2008), focus on a different set of corporate fundamentals unrelated to ours. Thus, the evidence presented in this paper sheds new light on the role of accounting-based corporate fundamentals in driving earnings forecast errors. Second, our findings provide further evidence on the role of information uncertainty, potentially caused by the volatility of a firm's underlying fundamentals and poor information, in evaluating a firm's value in light of new information. Finally, the presented evidence also provides new insights into the underlying cause of the value effect. It is still one of the biggest debates in finance whether the source of the value premium (i.e., the outperformance of value over growth stocks over longer horizons) is risk-based or a behavioural anomaly leading to mispricing. Our results suggest that mispricing in the form of earnings forecast errors should be taken into account when analysing the value effect.

The remainder of this paper is organised as follows. The next section discusses the related literature. Section 2.3 describes the sample data, the measurement of earnings forecast errors, and the methodology. Section 2.4 provides the empirical results of our estimated panel regression models, and Section 2.5 concludes.

2.2 Literature Review

Our study is related to three areas of the empirical finance and behavioural finance literature. First, we review and analyse the properties of earnings forecast errors. Second, we review the literature that links earnings forecast errors to firm characteristics. Here, we also briefly review the firm characteristics that underlie popular risk-factor models. Third, the role of information uncertainty is evaluated and serves as frame for our findings.

Starting with the properties of earnings forecast errors, Dechow & Sloan (1997) have analysed earnings forecasts, forecast errors, and their impact on stocks with an emphasis on the value premium. Based on data on listed U.S. stocks, they found that the realised mean annualised earnings-per-share (EPS) growth is approximately 9% below the predicted annualised EPS growth. Sorting all stocks based on their book-to-market ratio indicates that the negative forecast error increases monotonically going from value stocks to growth stocks. They further found that forecast errors are particularly high among stocks with high forecasted earnings growth. This supports the suggestion of Zhang (2006) as well as our findings that high-uncertainty firms are more likely to be growth firms (see below). When Dechow & Sloan (1997) linked forecasted earnings to stock prices, they initially mirrored virtually all forecasted EPS growth. As the EPS growth was subsequently realized at less than half the forecasted growth rate, they concluded that more than half of the value premium can be explained by the naive reliance of investors on biased earnings forecasts. However, a related study by Doukas, Kim, & Pantzalis (2002) failed to identify statistically significant differences in forecast errors between value and growth stocks.

Kothari et al. (2016) reviewed the literature related to the properties of analysts' forecasts and their links to corporate fundamentals. Forecast accuracy (i.e., the absolute difference between forecasted value and realised value) is linked to certain firm characteristics: Accuracy generally decreases with uncertainty measures, such as firm complexity and volatility in returns and earnings (Kross & Ro (1990), Huberts & Fuller (1995), Lang & Lundholm (1996)), which confirms our findings that growth stocks have higher uncertainty in their firm characteristics and higher earnings forecast errors. Accuracy is also negatively related to the forecast horizon, meaning that accuracy deteriorates when the forecast horizon increases (Sinha, Brown, & Das (1997), Clement (1999), Brown & Mohd (2003)). Overall, Kothari et al. (2016) concluded that forecasting accuracy seems to be a "firm characteristic influenced by firm-level attributes such as the riskiness of its investments, firm size, and temporary shocks" (Kothari et al., 2016, p. 6).

Looking at forecast bias (i.e., the sign of the difference between forecasted value and realised value), the empirical literature generally has found that analyst forecasts, especially long-term forecasts, are too optimistic. One reason for this is that analysts tend to produce too-optimistic forecasts for companies with less predictable earnings to secure access to managements' private information (Das, Levine, & Sivaramakrishnan (1998), Chen & Matsumoto (2006), Mayew (2008)). A related stream of research indicates that forecasts from analysts who are affiliated with an investment bank are systematically higher than forecasts from analysts not linked to an investment bank. Again, the rationale is to secure superior access to management's private information (e.g., Lin & McNichols (1998), Michaely & Womack (1999), Dechow, Hutton, & Sloan (2000), Agrawal & Chen (2008)).

Frankel & Lee (1998) were among the first to employ firm characteristics to predict future analyst forecast errors with a specific focus on identifying potential mispricing. They modelled realised two-year-ahead Return-on-Equity forecast errors with four firm characteristics, including book-to-price (B/P), five-year sales growth, and consensus long-term growth forecast.

While they found a negative relation between B/P and analyst forecast errors over specific forecast horizons, the relationship was not monotonic and did not hold across all tested horizons. Thus, they concluded “that the B/P effect is only tangentially related to forecast errors” (Frankel & Lee, 1998, p. 306). Sales growth was positively related to forecast errors, but the relationship was non-linear. Lastly, they also found that analyst forecasts tend to be more optimistic for firms with high long-term growth forecasts, confirming the findings of Dechow & Sloan (1997).

Hughes et al. (2008) analysed the predictability of analyst forecast errors by focussing on under-reaction and over-reaction variables identified in prior literature. The under-reaction variables included quarterly earnings surprises, past price changes and past earnings forecast revisions. Over-reaction variables include past sales growth, analysts’ long-term forecasts, change of property, plant and equipment and change of other long-term assets. All over-reaction variables had a negative relationship with analyst forecast errors, but the coefficients were mostly insignificant. The coefficients for the under-reaction variables were all highly significantly positive and in line with results reported in prior literature. Additionally, they found that accounting accruals were significantly negatively correlated with future analyst forecast errors. However, despite the “surprisingly large magnitude of predictable component estimates” (Hughes et al., 2008, p. 276) in analyst forecast errors, they found that this predictability did not automatically translate into profitable trading strategies.

So (2013) argued that the traditional approach of predicting analyst forecast errors used by Frankel & Lee (1998) and Hughes et al. (2008) is likely to suffer from omitted variable bias whenever the variables used to predict forecast errors correlate with unobservable inputs to analyst forecasts. He thus developed a new approach that aims to alleviate this bias by comparing forecasts based on firm characteristics with forecasts issued by analysts. For companies where the characteristics-based forecast exceeded the consensus analyst forecast, the subsequently realised earnings tended to exceed the consensus forecast, and vice versa.

This led to significant predictive power for both analyst forecast errors and future returns. For his characteristics forecast for future firms' EPS, So (2013) used the nine firm characteristics that also were applied by Fama & French (2006) to forecast profitability.² When So (2013) compared his characteristics approach to the traditional approach of Frankel & Lee (1998) and Hughes et al. (2008), he found that the coefficients of size, book-to-market, momentum, and the firm's most recent earnings surprise were significantly positive in regression results predicting analyst forecast errors. Additionally, total accruals and consensus long-term growth forecasts had a statistically significant negative coefficient. So (2013) also reported that the median analyst forecast tended to be above the forecast based on characteristics, consistent with the empirical finding that analysts are incentivised to produce optimistic forecasts.

Piotroski & So (2012) took a different approach by arguing that expectations embedded in different valuation multiples of value and growth stocks must be analysed in relation to the strength of the company's fundamentals. They measured the aggregate current strength of firm fundamentals based on nine variables related to profitability, changes in financial leverage and liquidity, and changes in operational efficiency.³ They documented that future expectation adjustments were significantly more pronounced for value stocks than for growth stocks when implied expectations were not in line with the recent strength in firm fundamentals. Consistent with this, they found that the return difference between value and growth stocks was strongest among firms where current valuation multiples were not in line with the recent aggregate strength in firm fundamentals. Among firms whose fundamental strength was largely in line with expectations implied by current valuations, the value premium was close to zero.

Additionally, Piotroski & So (2012) also used two non-return-based measures - consensus

²These include earnings per share, negative and positive accruals per share, percentage change in total assets, dividends per share, and book-to-market, amongst others.

³The nine variables are four profitability-related variables (return-on-assets, cashflow from operations scaled by total assets, change in net income, and accruals scaled by total assets); three variables related to changes in financial leverage and liquidity (change in the ratio of long-term debt to total assets, change in the ratio of current assets to current liabilities, and common equity issuance) and two operating efficiency-related variables (change in gross margin and change in the asset turnover ratio).

forecast errors and revisions in analysts' earnings forecasts - to derive expectation errors and expectation adjustments directly from analyst forecasts instead of deriving them from short-term stock price changes.⁴ The two measures were negative for the full sample and for most value and growth portfolios, meaning that analyst forecasts were, on average, too optimistic. Dividing each value and growth portfolio further into three sub-portfolios based on a firm's recent financial strength indicated that both consensus forecast errors and revisions in analyst earnings forecast were strongly negative for firms with weak financial strength, moderately negative for firms with average financial strength, and close to zero for firms with strong financial performance. Consensus forecast errors were only marginally less negative for value firms than for growth firms, but the difference was statistically insignificant. However, conditioning on a firm's recent financial strength reveals that growth firms with weak recent financials had the most negative consensus forecast errors while the forecast errors for value firms with strong financials were only marginally negative. Similarly, forecast revisions were the most negative for growth firms with weak recent financials but were close to zero for value firms with strong financials.

Next, we briefly review major risk-factor models and their underlying firm characteristics. Hou et al. (2017) compared the performance of the most prominent empirical asset pricing models in explaining 216 reported significant stock market anomalies between 1967 and 2014. The models included the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), which is just composed of the excess return on the market; the Fama & French (1993) three-factor model, which adds the size (market capitalisation) and value (book-to-market) risk factors; the Carhart (1997) four-factor model, which adds the cross-sectional momentum factor; the Pástor & Stambaugh (2003) four-factor model, which adds a liquidity factor to the Fama & French (1993) three-factor model; the Hou et al. (2015) q -factor model, consisting

⁴They define consensus forecast errors as firms' actual earnings next year minus the consensus forecast, scaled by total assets per share at the start of the portfolio formation period. The second non-return-based measure they use is revisions in analysts' earnings forecast, which is defined as total revision in the consensus forecast from the initial forecast measurement date until the firms' next annual earnings announcement date, also scaled by total assets per share (Piotroski & So, 2012, p. 2861).

of the market factor, a size factor, an investment factor based on Investment-to-Assets, and a profitability factor based on Return-on-Equity; and the Fama & French (2015) five-factor model, also consisting of the market factor, a size factor, an investment factor based on change in total assets, and a profitability factor based on Operating Profitability. Hou et al. (2017) found that their Hou et al. (2015) q -factor model performed best in explaining anomalies related to momentum and profitability while the Fama & French (2015) five-factor model outperformed slightly in explaining value-versus-growth anomalies. Overall, they concluded that corporate fundamentals such as investment and profitability, but not liquidity, are the main drivers of the cross-section of expected returns.

Third, the role of information uncertainty, which serves as a frame for our findings, is evaluated. Several papers, including Kothari et al. (2016), posit that the forecast accuracy generally decreases with uncertainty measures. Zhang (2006) examined the role of information uncertainty in short-term stock price continuation anomalies as well as cross-sectional variations in stock returns. He defined information uncertainty as “ambiguity with respect to the implications of new information for a firm’s value” where the ambiguity can potentially stem from two sources: volatility of a firm’s underlying fundamentals and poor information (Zhang, 2006, p. 105). As information uncertainty is not directly measurable, he used six proxies for information uncertainty (firm size, firm age, analyst coverage, dispersion in analyst forecasts, stock volatility, and cash flow volatility) as well as analyst forecast revisions and price momentum to differentiate between good and bad news. The two main findings were, first, that the initial market reaction to new public information was far from complete, implying that bad news predicts lower future returns and vice versa. Second and more importantly, the degree of incompleteness rose monotonically with the degree of information uncertainty. Based on this, Zhang (2006) argued that investors underreact more to new information when there is higher uncertainty. Thus, the market reaction is far from complete for high-uncertainty stocks, and he suggested that high-uncertainty firms are more likely

to be growth firms. This argumentation is underpinned by the theoretical model of Daniel, Hirshleifer, & Subrahmanyam (1998) and Daniel, Hirshleifer, & Subrahmanyam (2001), where they argued that investors become overconfident about their private information and under-react to public signals such as analyst forecast revisions when firms have greater information uncertainty and are thus difficult to value. In a similar vein, Hirshleifer (2001) argued that a lack of accurate feedback about a firm’s fundamentals leaves room for behavioural biases. Thus, any misvaluation effects should be strongest among companies with high uncertainty and poor information.

2.3 Data and Methodology

2.3.1 Corporate Fundamentals and Stock Data

We obtained data on corporate fundamentals from the CRSP/Compustat Merged - Fundamentals Annual and Quarterly database for the period January 1981 – December 2017. To allow for comparisons with the studies closely related to ours, we follow Xing (2008), Piotroski & So (2012), and Hou et al. (2015) and excluded observations from financial firms (Standard Industrial Classification codes between 6000 and 6999) in our sample. Moreover, we follow Fama & French (2015) and include only ordinary common shares with the Centre for Research in Security Practices (CRSP) share code 10 (NYSE common shares excluding foreign, ADRs, REITs and Closed-End Funds) or 11 (NYSE/NYSE American common shares excluding foreign, ADRs, REITs, and Closed-End Funds).

Every year, we categorize firms into 25 portfolios based on their book-to-market ratio and firm size to draw conclusions about the average earnings forecast errors for these classes of stocks. This is a standard approach in asset pricing, which reduces the variability in measures such as earnings forecast errors. Additionally, the classification into portfolios allows for comparisons between value and growth stocks as well as between large caps and small caps. The construction and timing of the 25 size and book-to-market portfolios follows Fama &

French (1993), which is also applied by Xing (2008), Fama & French (2015), and Hou et al. (2015). The portfolios are constructed at the end of each June as the intersections of five portfolios formed on firm size (by market value of equity, ME) and five portfolios formed on the book-to-market ratio. To construct the book-to-market ratio (BE/ME) in June of year t the book value of equity (BE) is taken at the end of the fiscal year ending in year $t-1$, and the market value of equity (ME) is taken at the end of December of year $t-1$. The size breakpoints for year t are the NYSE market equity quintiles at the end of June of year t . The BE/ME breakpoints are also based on NYSE quintiles. The final sample is composed of 52,630 firm-year observations spanning the portfolio formation years 1982-2016.

Following Fama & French (1993) and Xing (2008), we define the book value of equity (BE) as the Compustat book value of common equity (Compustat annual data item 60) plus balance-sheet deferred taxes (data item 74) and investment tax credits (data item 208), minus the book value of preferred stock. Depending on data availability, we use the redemption (data item 56), liquidation (data item 10), or par value (data item 130) of preferred stock. We follow Xing (2008), Piotroski & So (2012), and Hou et al. (2015) and exclude firms with a negative or zero book value of equity which removes 8,395 (0.35%) firm-year observations from our sample.

Among the corporate fundamentals we analyse the role of three investment-based characteristics. Investment-to-Assets (I/A) in portfolio formation year t is defined as the annual change in total assets (Compustat annual item AT) divided by one-fiscal-year lagged total assets (Hou et al. (2015), Fama & French (2015)):

$$\text{Investment to Assets (I/A)}_t = \frac{AT_{t-1} - AT_{t-2}}{AT_{t-2}}$$

The investment factor in the four-factor q -model from Hou et al. (2015) is based on sorts of Investment-to-Assets (I/A). The second investment-related measure is Investment Growth (IG). For the portfolio formation year t , it is the growth rate in capital expenditure (Compustat

annual item CAPX) from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in $t-1$ (Hou et al. (2015), Fama & French (2015)):

$$\text{Investment Growth } (IG)_t = \frac{CAPX_{t-1}}{CAPX_{t-2}} - 1$$

Lastly, Investment-to-Capital (I/K) in year t is taken from Xing (2008) and is defined as capital expenditures (Compustat data item CAPX) divided by the net book value of property, plant, and equipment (data item 8, PPENT) using data from fiscal year ending in $t-1$:

$$\text{Investment - to - Capital } (I/K)_t = \frac{CAPX_{t-1}}{PPENT_{t-1}}$$

Table 1 shows simple time-series averages as well as Newey & West (1994) heteroskedasticity and autocorrelation consistent (HAC) standard errors (in parentheses) of the investment measures. In line with Xing (2008), small firms and growth firms have higher Investment Growth rates as well as higher Investment-to-Capital ratios than large companies and value companies. A similar picture can be seen for the Investment-to-Assets ratio across growth and value firms, but the difference vanishes between small and large firms as the book-to-market ratio increases. Table 1 further shows that growth stocks carry a higher volatility in their investment measures. This effect tends to be stronger for small-growth stocks than for large-growth stocks, which supports the argumentation of Zhang (2006) that small-growth stocks have a higher information uncertainty as they have less information available to the market.

Additionally, we use three measures of profitability. The definition of Operating Profitability (OP) follows Fama & French (2015): In the sort for June of year t , it is measured with accounting data for the fiscal year ending in $t-1$ and is defined as total revenues (data item REVT) minus cost of goods sold (data item COGS); minus selling, general, and administrative expenses (data item XSGA); minus interest expense (data item XINT); all divided by book

Table 1: Summary statistics for investment measures

	Investment-to-Assets					Investment Growth					Investment-to-Capital				
	Low B/M	2	3	4	High B/M	Low B/M	2	3	4	High B/M	Low B/M	2	3	4	High B/M
Small	31.72 (2.47)	21.95 (2.1)	16.52 (2.12)	12.34 (2.78)	7.21 (1.73)	92.06 (5.77)	59.04 (5.96)	44.71 (3.55)	33.84 (4.51)	22.90 (3.8)	37.93 (1.23)	32.80 (1.33)	28.04 (0.74)	24.62 (0.94)	21.52 (1.02)
2	32.14 (2.62)	23.14 (2.79)	15.91 (2.78)	10.68 (1.26)	7.74 (1.68)	71.78 (6.35)	46.44 (6.4)	31.16 (4.75)	21.18 (2.64)	14.37 (1.92)	36.78 (0.93)	29.20 (1.48)	24.97 (0.94)	20.77 (0.99)	18.05 (0.77)
3	31.64 (3.46)	17.61 (2.11)	13.63 (1.85)	11.65 (1.86)	9.04 (1.61)	55.56 (4.35)	29.80 (3.21)	23.22 (4.4)	14.84 (2.03)	14.61 (4.7)	33.93 (1.16)	25.29 (0.72)	22.04 (0.93)	18.24 (0.78)	17.94 (1.11)
4	25.10 (4.68)	14.74 (1.19)	12.19 (1.71)	11.49 (1.56)	10.39 (1.09)	40.87 (5.42)	20.55 (2.91)	15.28 (3.04)	14.74 (3.01)	11.14 (2.07)	30.54 (1.95)	23.02 (0.58)	20.24 (0.82)	17.26 (0.93)	14.05 (0.55)
Big	16.99 (1.76)	13.84 (2.48)	12.78 (4.84)	15.41 (2.73)	13.43 (2.3)	19.06 (2.21)	13.11 (2.03)	14.75 (4.5)	14.19 (4.05)	10.37 (2.96)	26.32 (0.86)	21.68 (0.85)	17.27 (0.77)	15.13 (0.93)	13.60 (1.02)

The table shows simple time-series averages as well as Newey & West (1994) heteroskedasticity and autocorrelation consistent (HAC) standard errors (in parentheses) of the investment measures for the 35 portfolio formation years 1982-2016. All investment-based measures are trimmed every year at the 1% and 99% levels, see figure 1 for the effect of trimming on the investment measures. Investment-to-Assets, I/A, is defined as the annual change in total assets (Compustat annual item AT) divided by one-year lagged total assets. Investment growth (IG) in the portfolio formation year t it is the growth rate in capital expenditure (Compustat annual item CAPX) from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in $t-1$. Investment-to-Capital (I/K) is defined as capital expenditures (Compustat data item CAPX) divided by the net book value of property, plant, and equipment (data item 8, PPENT).

value of equity (BE). It requires non-missing data for at least one of the following: cost of goods sold; selling, general and administrative expenses; or interest expense.

$$\text{Operating Profitability (OP)}_t = \frac{REVT_{t-1} - COGS_{t-1} - XSGA_{t-1} - XINT_{t-1}}{BE_{t-1}}$$

The calculation of Gross Profitability (GP) in year t is based on Novy-Marx (2013) and is defined as revenues (REVT) minus cost of goods sold (COGS) scaled by total assets (AT), all measured in fiscal year ending in year $t-1$:

$$\text{Gross Profitability (GP)}_t = \frac{REVT_{t-1} - COGS_{t-1}}{AT_{t-1}}$$

Hou et al. (2015) measure profitability as Return-on-Equity (ROE), which is income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged book equity. The profitability factor in the q -model from Hou et al. (2015) is based on sorts of Return-on-Equity (ROE). We use the annual equivalents of these variables to align the frequency with all other corporate fundamentals. Thus, we measure Return-on-Equity in portfolio formation year t as annual Income Before Extraordinary Items (Compustat annual

data item IB) measured in fiscal year ending in $t-1$ divided by book value of equity measured in fiscal year $t-2$:

$$\text{Return-on-Equity (ROE)}_t = \frac{IB_{t-1}}{BE_{t-2}}$$

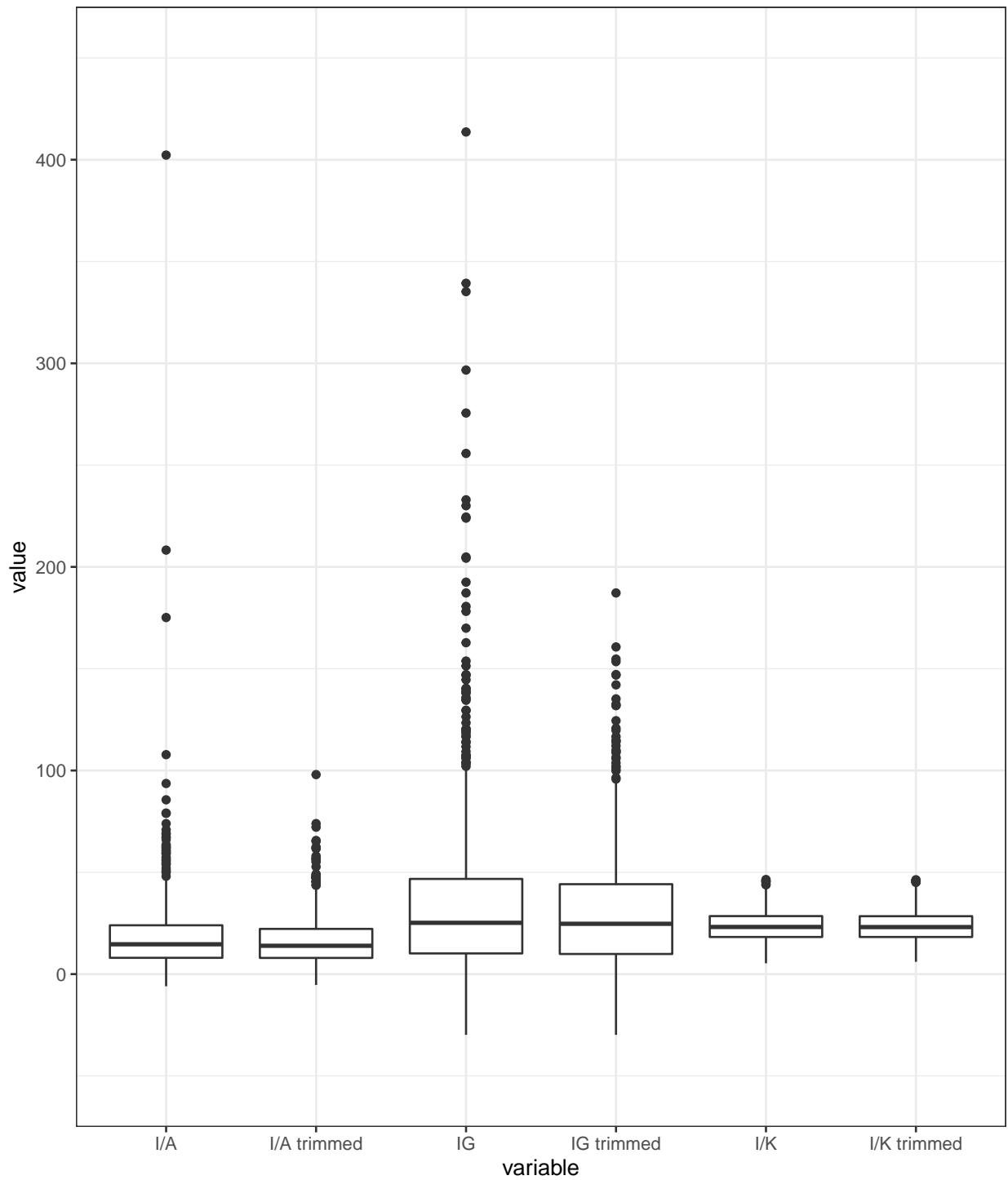
Following Novy-Marx (2013), all investment- and profitability-based measures are trimmed every year at the 1% and 99% levels to remove the effect of outliers and data errors. Figure 1 depicts the effect of trimming on the investment measures while Figure 2 illustrates the effect for the profitability measures. Table 2 indicates that growth firms have a higher gross profitability compared to value firms across all size quintiles, which confirms the findings of Novy-Marx (2013). Additionally, growth firms have a higher operating profitability as well as a higher Return-on-Equity. The only exception is the small-growth portfolio, which has a very low operating profitability and is the only portfolio with a negative Return-on-Equity, on average. Similar to the investment measures, growth stocks also have a much higher volatility in their profitability measures compared to value stocks, especially the small-growth portfolio, leading to higher information uncertainty.

Table 2: Summary statistics for profitability measures

	Operating Profitability					Gross Profitability					Return-on-Equity				
	Low B/M	2	3	4	High B/M	Low B/M	2	3	4	High B/M	Low B/M	2	3	4	High B/M
Small	6.53 (10.38)	18.53 (2.09)	18.26 (1.81)	17.32 (1.03)	13.39 (0.68)	41.19 (2.69)	43.71 (1.33)	39.88 (0.96)	35.92 (0.72)	32.19 (0.97)	-6.95 (7.04)	8.71 (1.83)	6.70 (1.41)	5.20 (1)	1.36 (0.97)
2	25.82 (2.24)	25.60 (0.72)	22.16 (0.58)	20.05 (0.65)	14.80 (0.9)	47.28 (2.32)	43.51 (1.32)	37.96 (1.53)	31.41 (0.86)	24.85 (1.07)	6.12 (4.3)	12.34 (0.94)	10.28 (0.61)	7.10 (0.73)	3.81 (0.46)
3	37.92 (2.8)	28.16 (0.45)	24.58 (0.63)	21.18 (0.58)	16.04 (1.01)	48.40 (2)	41.49 (1.46)	34.78 (1.14)	25.52 (0.53)	20.75 (0.79)	16.09 (1.65)	14.26 (0.5)	10.80 (0.65)	7.28 (1.07)	4.19 (1.4)
4	48.69 (3.4)	30.25 (0.56)	25.58 (0.58)	21.61 (1.11)	16.82 (0.55)	50.73 (5.9)	39.25 (1.95)	30.72 (1.26)	21.76 (0.72)	17.17 (0.8)	23.71 (0.95)	14.96 (0.55)	10.86 (0.94)	7.46 (1.02)	5.50 (0.4)
Big	49.57 (7.6)	32.34 (1.09)	26.81 (1.24)	22.63 (1.41)	17.71 (0.83)	52.38 (8.77)	34.08 (3.8)	25.60 (2.37)	19.72 (1.66)	15.11 (1.19)	28.62 (1.44)	16.85 (0.71)	12.53 (0.96)	8.03 (1.62)	6.35 (0.82)

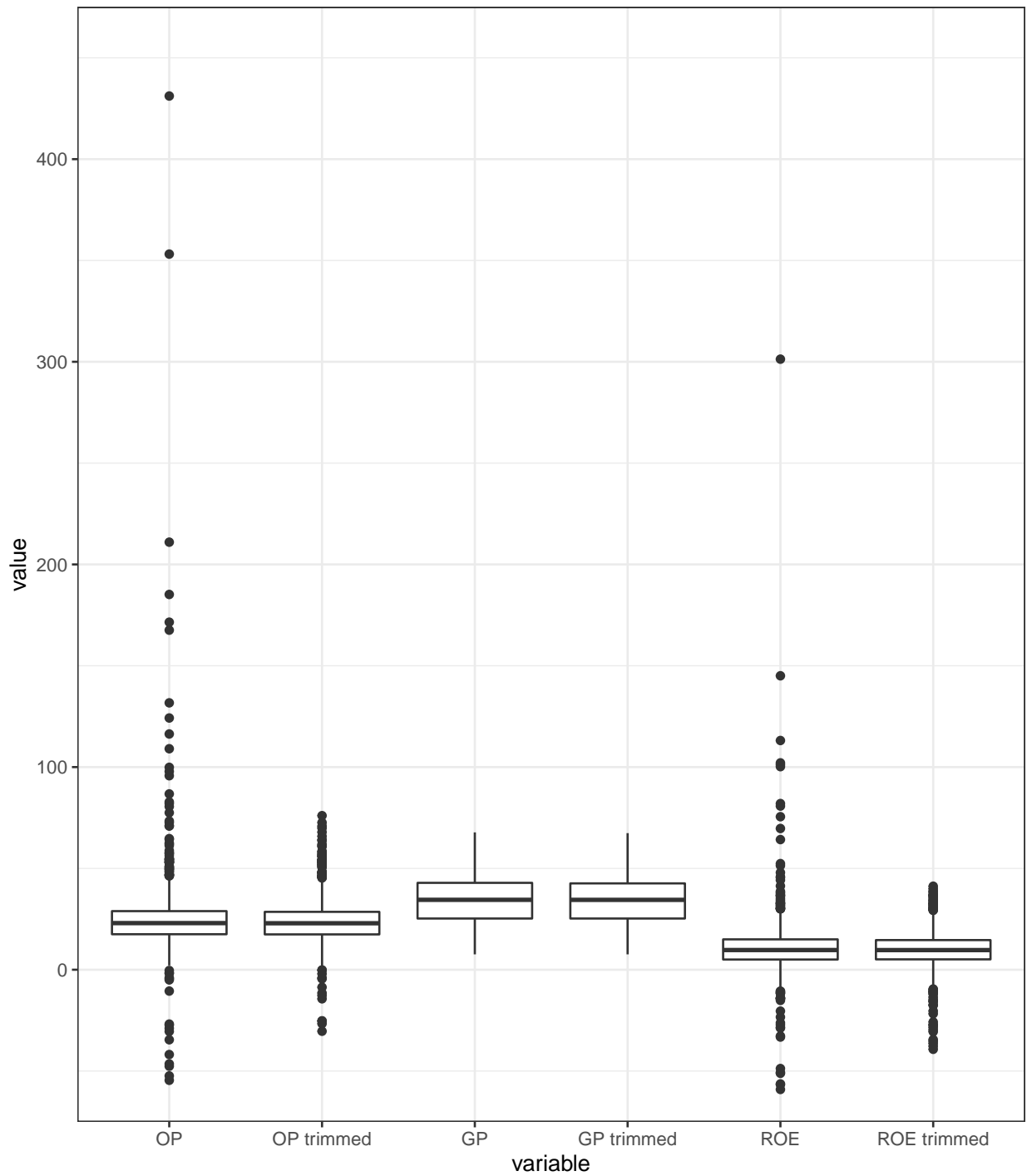
The table shows simple time-series averages as well as Newey & West (1994) heteroskedasticity and autocorrelation consistent (HAC) standard errors (in parentheses) of the profitability measures for the 35 portfolio formation years 1982-2016. All profitability measures are trimmed every year at the 1% and 99% levels, see figure 2 for the effect of trimming on the profitability measures. Operating profitability, OP, in the sort for June of year t is measured with accounting data for the fiscal year ending in year $t-1$ and is defined as revenues (Compustat annual item REVT) minus cost of goods sold (COGS), minus selling, general, and administrative expenses (XSGA), minus interest expense (XINT) all divided by book value of equity. It requires non-missing data for at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expense. Gross Profitability (GP) is defined as revenues (REVT) minus cost of goods sold (COGS) scaled by total assets (AT). Return-on-Equity (ROE) is income before extraordinary items (IB) divided by lagged book equity.

Stock data is from the CRSP/Compustat Merged - Security Monthly Database. The monthly excess total returns are calculated as monthly total returns from the CRSP minus the risk-free



The graph shows the distribution of the investment measures for 25 portfolios formed on size and book-to-market for the 35 portfolio formation years 1982–2016. The trimmed versions of all investment measures are trimmed every year at the 1% and 99% levels. The lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). The upper whisker extends from the hinge to the largest value no further than $1.5 \times \text{IQR}$ from the hinge (where IQR is the inter-quartile range, or distance between the first and third quartiles). The lower whisker extends from the hinge to the smallest value at most $1.5 \times \text{IQR}$ of the hinge. Data beyond the end of the whiskers are called outlying points and are plotted individually. Investment-to-Assets (I/A) is defined as the annual change in total assets (Compustat annual item AT) divided by one-year lagged total assets. Investment growth (IG) in the portfolio formation year t is the growth rate in capital expenditure (Compustat annual item CAPX) from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in $t-1$. Investment-to-Capital (I/K) is defined as capital expenditures (Compustat data item CAPX) divided by the net book value of property, plant, and equipment (data item 8, PPENT). The y-axis is limited to -50 and 450 .

Figure 1: Effect of trimming on investment measures



The graph shows the distribution of the profitability measures for 25 portfolios formed on size and book-to-market for the 35 portfolio formation years 1982–2016. The trimmed versions of all profitability measures are trimmed every year at the 1% and 99% levels. The lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). The upper whisker extends from the hinge to the largest value no further than $1.5 \times \text{IQR}$ from the hinge (where IQR is the inter-quartile range, or distance between the first and third quartiles). The lower whisker extends from the hinge to the smallest value at most $1.5 \times \text{IQR}$ of the hinge. Data beyond the end of the whiskers are called outlying points and are plotted individually. Operating profitability (OP) in the sort for June of year t is measured with accounting data for the fiscal year ending in year $t-1$ and is defined as revenues (Compustat annual data item REV_T) minus cost of goods sold, minus selling, general, and administrative expenses (COGS), minus interest expense (XINT) all divided by book value of equity. It requires non-missing data for at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expense. Gross Profitability (GP) is defined as revenues (REV_T) minus cost of goods sold (COGS) scaled by total assets (AT). Return-on-Equity (ROE) is income before extraordinary items (Compustat annual item IB) divided by lagged book equity. The y-axis is limited to -50 and 450.

Figure 2: Effect of trimming on profitability measures

rate, which is downloaded from Kenneth R. French’s website.⁵ Similar to Fama & French (1993) and Hou et al. (2015), we calculate value-weighted portfolio excess returns from July of year t to June of $t+1$, and the portfolios are rebalanced at the end of June $t+1$. As the last characteristic, we define Portfolio Momentum as past 12-month cumulative total portfolio return but skipping the return for the most recent month for each portfolio. Specifically, Portfolio Momentum in June t is the cumulative portfolio total return from July of year $t-1$ to May of year t . Skipping the return of the most recent month is standard in the momentum literature to avoid the documented one-month short-term stock reversal effect (see Jegadeesh & Titman (1993), Fama & French (1996), Grinblatt & Moskowitz (2004), Asness, Moskowitz, & Pedersen (2013)).

Table 3 illustrates that value firms have higher monthly excess returns than growth firms for every size quintile except for large firms. This confirms the well-known value effect, i.e. that stocks with high book-to-market ratios have higher average returns than stocks with low book-to-market ratios, which has been identified in many empirical studies (Basu (1977), Fama & French (1992), Xing (2008), Cochrane (2011); amongst others). Furthermore, Table 3 confirms the empirical finding that stocks from small companies earn higher returns than stocks from large firms, on average. This holds for every book-to-market quintile except for growth stocks and confirms the empirical finding that the small-firm effect did not persist for growth firms after it had been first identified by Banz (1981), see Chen & Zhao (2009).

2.3.2 The Measurement of Earnings Forecast Errors

Earnings forecast errors (*EFE*) have been put forward as one potential measure of a mispricing-based explanation of the value premium in the literature; see Piotroski & So (2012). The advantage of earnings forecast errors is that it is a non-return-based measure. Thus, it allows for a direct analysis of expectation errors caused by institutional investors and analysts instead of deriving them indirectly from short-term stock price changes. One

⁵http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 3: Summary statistics for portfolios

	monthly excess returns					book-to-market ratio					market capitalisation				
	Low B/M	2	3	4	High B/M	Low B/M	2	3	4	High B/M	Low B/M	2	3	4	High B/M
Small	0.76 (0.38)	1.02 (0.32)	1.07 (0.33)	1.19 (0.33)	1.21 (0.38)	0.22 (0.02)	0.43 (0.03)	0.62 (0.04)	0.86 (0.04)	1.53 (0.09)	0.21 (0.13)	0.20 (0.14)	0.20 (0.15)	0.19 (0.13)	0.18 (0.09)
2	0.71 (0.29)	0.93 (0.25)	1.04 (0.26)	0.83 (0.26)	0.85 (0.34)	0.22 (0.02)	0.43 (0.03)	0.62 (0.04)	0.84 (0.04)	1.41 (0.08)	0.58 (0.61)	0.58 (0.44)	0.58 (0.46)	0.57 (0.44)	0.55 (0.39)
3	0.73 (0.3)	0.95 (0.29)	0.81 (0.25)	0.96 (0.29)	1.17 (0.29)	0.21 (0.02)	0.43 (0.03)	0.61 (0.04)	0.85 (0.04)	1.37 (0.05)	1.31 (1.07)	1.30 (0.9)	1.28 (0.99)	1.29 (0.9)	1.26 (1.04)
4	0.83 (0.28)	0.88 (0.22)	0.86 (0.27)	0.87 (0.27)	1.10 (0.27)	0.22 (0.02)	0.42 (0.03)	0.62 (0.04)	0.85 (0.04)	1.36 (0.07)	3.28 (3.69)	3.21 (4.11)	3.09 (6.85)	3.01 (2.54)	3.16 (14.17)
Big	0.82 (0.23)	0.76 (0.22)	0.75 (0.2)	0.75 (0.22)	0.67 (0.26)	0.21 (0.02)	0.42 (0.03)	0.62 (0.04)	0.85 (0.04)	1.26 (0.06)	78.25 (27.95)	80.17 (32.09)	49.28 (31.66)	42.81 (31.05)	35.50 (25.32)

The table shows in the first panel the average monthly excess returns and standard errors (in parentheses) for 25 portfolios formed on size and book-to-market for the period July 1982 - June 2017 (420 months). The second and third panel shows the time-series averages of book-to-market ratios and market capitalisation (in billion of US-Dollars) including standard errors (in parentheses) for the 35 portfolio formation years 1982-2016. The portfolios are constructed at the end of each June as the intersections of five portfolios formed on firm size (market value of equity, ME) and five portfolios formed on the book-to-market ratio (BE/ME). To construct the book-to-market ratio in June of year t the book value of equity is taken at the end of the fiscal year ending in year $t-1$ and the market value of equity is taken at the end of December of $t-1$. The size breakpoints for year t are the NYSE market equity quintiles at the end of June of t .

restriction is that analyst forecasts are not available for all firms, and the sample will be biased towards larger, more profitable firms (Lang & Lundholm, 1996). In our sample, of 122950 firm-year observations with valid corporate fundamental data, 52630 observations (42.81%) also have earnings forecast errors data.

In line with the timing of the portfolio formation, we measure earnings forecast errors every year in June. Following Piotroski & So (2012), we define earnings forecast errors (EFE) in year t for an individual company as the firms' actual trailing 12-month earnings per share measured in June $t+1$, minus consensus 12-month expected earnings per share measured in June t , scaled by total assets per share in year t :

$$EFE_t = \frac{12m \text{ earnings per share}_{t+1} - \text{consensus } 12m \text{ expected earnings per share}_t}{\text{total assets per share}_t}$$

We use shares outstanding from the CRSP to calculate total assets per share, which is also used to calculate the market value of equity (ME) in the BE/ME ratio. Thus, for consistency, this measure of shares outstanding is preferred. Similar to the investment and profitability measures, in a next step earnings forecast errors are trimmed every year at the 1% and 99% levels to remove the effect of outliers and data errors. In a final step and also similar to the

investment and profitability measures, earnings forecast errors in year t for the 25 size- and book-to-market-sorted portfolios are calculated as the value-weighted average of the earnings forecast errors of all stocks in each portfolio based on the market value of equity (ME) in June of year t for each stock. Research reveals that the accuracy of forecasts deteriorates over longer forecast horizons (Brown & Mohd, 2003; Clement, 1999; Sinha et al., 1997). Taking this into consideration, we focus on forecasts with a one-year horizon.

Table 4: Earnings forecast errors across portfolios

	Low B/M	2	3	4	High B/M	t-stat (High- Low) B/M
Small	-3.97 (0.43)	-2.15 (0.25)	-1.43 (0.1)	-1.24 (0.06)	-0.94 (0.11)	9.18 (0)
2	-2.42 (0.47)	-1.20 (0.17)	-0.85 (0.11)	-0.75 (0.05)	-0.73 (0.08)	6.71 (0)
3	-1.51 (0.26)	-0.71 (0.09)	-0.72 (0.11)	-0.46 (0.1)	-0.37 (0.1)	4.24 (0)
4	-0.83 (0.11)	-0.47 (0.09)	-0.43 (0.1)	-0.42 (0.09)	-0.52 (0.13)	1.5 (0.14)
Big	-0.29 (0.05)	-0.17 (0.09)	-0.17 (0.09)	-0.30 (0.09)	-0.19 (0.08)	0.84 (0.4)

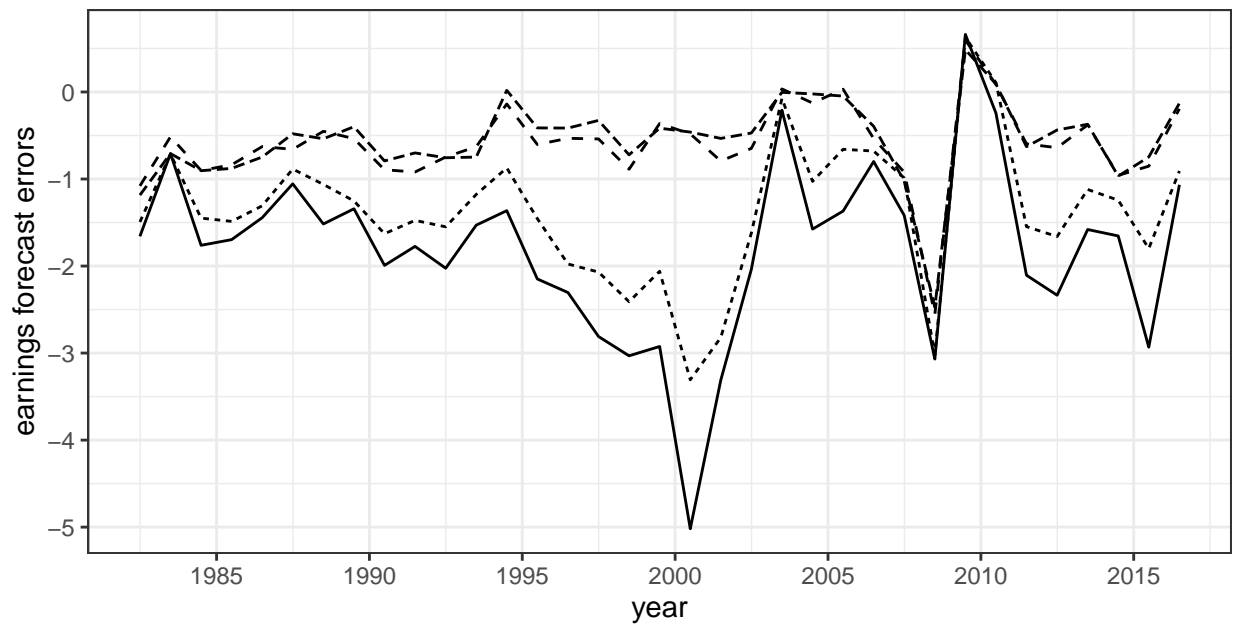
The table shows the time-series averages as well as Newey & West (1994) heteroskedasticity and autocorrelation consistent (HAC) standard errors (in parentheses) of the value-weighted earnings forecast errors for the 25 portfolios formed on size and book-to-market for the 35 portfolio formation years 1982-2016. The last column shows t-statistics and p-values (in parentheses) of testing the equality of earnings forecast errors for the high B/M portfolio and the low B/M portfolio for each size bucket. Earnings forecast errors for an individual company in the sort for June of year t is defined as firms' actual trailing 12 month earnings per share measured in June $t+1$ minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t . Earnings forecast errors are trimmed every year at the 1% and 99% levels.

Table 4 illustrates that the mean values of earnings forecast errors are negative for all portfolios, meaning that analysts' forecasts are, on average, too high; this confirms the findings of Dechow & Sloan (1997) and Kothari et al. (2016), amongst others. The magnitude of this bias varies by book-to-market ratio and size: Earnings forecast errors are much higher (meaning, more negative) for growth stocks than for value stocks. The last column in Table 4 shows that the difference in earnings forecast errors between value and growth stock portfolios

is statistically significant (at the 5% level) for the smallest three size quintiles but not among large-cap stocks. Earnings forecast errors also increase almost linearly, going from small to large firms across all book-to-market quintiles, meaning that analyst forecasts of earnings are more optimistic for small firms compared to large firms, on average. The small-growth portfolio has, by far, the most negative earnings forecast errors. Dechow & Sloan (1997) also find much higher (meaning, more negative) earnings forecast errors for growth stocks than for value stocks. Piotroski & So (2012) also report analyst forecast errors across growth, middle, and value portfolios with no further distinction between firm size. They also find that analyst forecast errors for value stocks marginally exceed those for growth stocks, but the difference is not statistically significant. However, conditioning on the firm's recent financial strength reveals that growth stocks with weak financials have the largest negative forecast errors while value firms with strong financials have forecast errors that are only marginally negative.

Figures 3 and 4 show simple time series averages of analyst forecast errors for groups of value and growth stock portfolios as well as groups of small and large market capitalisation stock portfolios. Of the 25 size and book-to-market sorted portfolios, the five (10) portfolios with the lowest book-to-market ratio are classified as "Growth Top 20" ("Growth Top 40"). Similarly, the five (10) portfolios with the highest book-to-market ratio are classified as "Value Top 20" ("Value Top 40"). Figure 3 indicates that the earnings forecast errors for value portfolios are always quite stable around -0.5. The only exception is the global financial crisis in 2008, which was totally unexpected to analysts, at least judged by earnings forecast errors. For the growth-oriented portfolios, the earnings forecast errors are always below the measure for value portfolios. In addition to the global financial crisis in 2008, analysts also massively overestimated earnings for growth stocks at the time the dot-com bubble burst in 2000, which led to very negative earnings forecast errors at that time. This effect is especially pronounced for the most growth-oriented portfolios ("Growth Top 20").

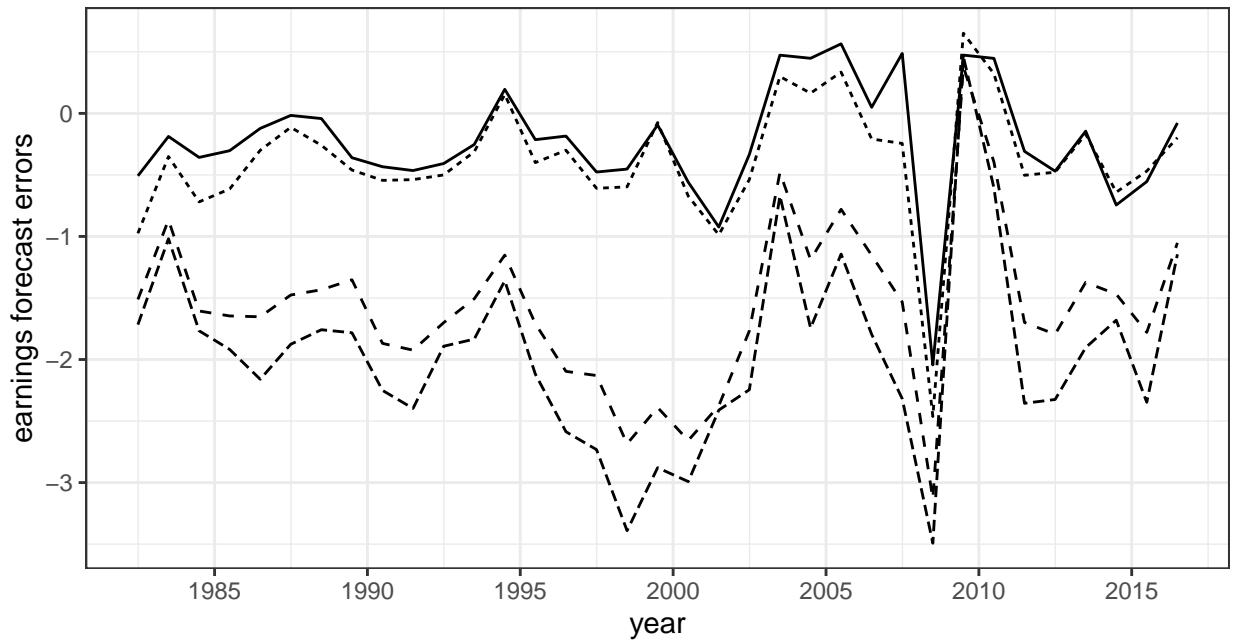
In a similar vein, Figure 4 illustrates the average earnings forecast errors across small and



linetype — Growth Top 20 Growth Top 40 -.- Value Top 20 - - Value Top 40

The figure shows time series of the average earnings forecast errors across portfolios formed on size and book-to-market for the 35 portfolio formation years 1982–2016. Out of the 25 size and book-to-market sorted portfolios, the five (10) portfolios with the lowest book-to-market ratio are classified as Growth Top 20 (Growth Top 40). Similarly, the five (10) portfolios with the highest book-to-market ratio are classified as Value Top 20 (Value Top 40). Earnings forecast errors in the sort for June of year t for an individual company are defined as firms' actual trailing 12 month earnings per share measured in June $t+1$ minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t . Earnings forecast errors are trimmed every year at the 1% and 99% levels.

Figure 3: Earnings forecast errors for growth and value portfolios



linetype — Big Top 20 Big Top 40 -.- Small Top 20 - - Small Top 40

The figure shows time series of the average earnings forecast errors across portfolios formed on size and book-to-market for the 35 portfolio formation years 1982–2016. Out of the 25 size and book-to-market sorted portfolios, the five (10) portfolios with the lowest market capitalisation are labelled as Small Top 20 (Small Top 40). Similarly, the five (10) portfolios with the highest market capitalisation are labelled as Big Top 20 (Big Top 40). Earnings forecast errors in the sort for June of year t for an individual company are defined as firms' actual trailing 12 month earnings per share measured in June $t+1$ minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t . Earnings forecast errors are trimmed every year at the 1% and 99% levels.

Figure 4: Earnings forecast errors for small and big portfolios

large stock portfolios. Of the 25 size and book-to-market sorted portfolios, the five (10) portfolios with the lowest market capitalisation are labelled as “Small Top 20” (“Small Top 40”). Similarly, the five (10) portfolios with the highest market capitalisation are labelled as “Big Top 20” (“Big Top 40”). Analogous to value stocks, Figure 4 illustrates that the earnings forecast errors for large-cap portfolios are always quite stable around -0.5. The only exception is the global financial crisis in 2008, which, again, came totally unexpected to analysts covering large-cap stocks. The earnings forecast errors for small-cap portfolios are always below the measure for large-cap portfolios. In addition to the global financial crisis in 2008, analysts also massively overestimated earnings for small-cap stocks when the dot-com bubble burst. This effect is especially pronounced for portfolios with the smallest market capitalisation stocks (“Small Top 20”) and mirrors the findings for the growth portfolios.

2.3.3 Methodology

We estimate panel regression models with earnings forecast errors (EFE) as the dependent variable and corporate fundamentals individually as well as combinations thereof as the explanatory variables. To address potential problems related to omitted variable bias, we include both entity (portfolio) fixed effects as well as time fixed effects. Entity fixed effects control for variables that vary across portfolios but are constant over time within a portfolio. Time fixed effects control for variables that are constant across portfolios but change over time. This could be, for example, changes in the skill set of analysts who provide earnings estimates, changes in the compensation structure for analysts, or changes in regulations affecting all companies and industries. The entity (portfolio) and time fixed effects regression model with one explanatory variable is defined as

$$EFE_{it} = \beta_1 X_{it} + \alpha_i + \lambda_t + u_{it}$$

where EFE_{it} are the earnings forecast error of portfolio i in time period t , X_{it} is the value of the single regressor for entity i in time period t , α_i is the entity (portfolio) fixed effect, and λ_t is the time fixed effect. In the case of combinations of corporate fundamentals, the panel regression model extends to

$$EFE_{it} = \beta_1 X_{1,it} + \dots + \beta_k X_{k,it} + \alpha_i + \lambda_t + u_{it}$$

where $X_{1,it}$ is the value of the first regressor for entity i in time period t , $X_{2,it}$ is the value of the second regressor, and so forth.⁶ The error term u_{it} is assumed to have a conditional mean of zero, given all observations of X for that portfolio.

As the residuals are likely to be correlated across both entity (portfolio) and time, we double-cluster the standard errors at the entity (portfolio) level and the time dimension. This is the recommended procedure from the seminal papers of Petersen (2009) and Thompson (2011) on estimating standard errors in finance panel data and is based on the assumption that market-wide shocks, such as changes in regulations or taxes, will likely induce correlation between firms (and thus portfolios) at a specific point in time, which requires clustering at the time dimension. Furthermore, persistent common shocks, such as business cycle fluctuations, may lead to residuals being correlated between different firms (and thus portfolios) over successive time periods, which warrants clustering at the entity (portfolio) level as well (Thompson, 2011, p. 1). Clustered standard errors are generally valid in the presence of heteroskedasticity, autocorrelation, or both (Stock & Watson, 2015, p. 413). Additionally, double-clustering is most applicable when the number of observations in both dimensions (portfolio and time, in this case) is not too far apart (Thompson, 2011, p. 2). Our data is composed of 25 portfolios and 35 year observations, which makes it well-suited for double-clustering.

In a further analysis, we separately analyse the effect of corporate fundamentals on earnings forecast errors for value and growth stocks separately. Among the 25 portfolios formed

⁶The notation of the panel regression model follows Stock & Watson (2015).

on size and book-to-market, within each size quintile the two portfolios with the lowest book-to-market ratio are classified as growth portfolios. Similarly, within each size quintile the two portfolios with the highest book-to-market ratio are classified as value portfolios. Thus, among the 25 portfolios, 10 are classified as growth, 10 as value, and the middle five portfolios are left out in this analysis.

2.4 Empirical Results

The results across all 25 portfolios formed on size and the book-to-market ratio with earnings forecast errors as the dependent variable are depicted in Table 5.⁷ Models (1)–(3) indicate the effect of each of the three investment-based measures individually on earnings forecast errors. The coefficient for each investment-related measure is negative and statistically significant ($p < 0.1$ for Investment-to-Assets, $p < 0.05$ for Investment Growth and $p < 0.01$ for Investment-to-Capital). This implies that higher corporate investments lead analysts to overestimate next-period earnings, on average, which results in more negative earnings forecast error, *ceteris paribus*. Higher corporate investments seem to be associated with higher earnings growth expectations that do not materialise, at least not in the following year. The results for the investment-related measures change somewhat when we employ all three variables combined in model (4): The coefficients for Investment-to-Assets and Investment Growth decline substantially in magnitude and become statistically insignificant. However, the coefficient for Investment-to-Capital remains highly significant ($p < 0.01$) and stable (-5.900 when regressed individually versus -5.378 when combined with the other two investment measures). Thus, the Investment-to-Capital ratio proposed by Xing (2008) contains information that is superior to the information content in the other two investment-related measures in predicting earnings forecast errors. These results are in line with the findings of Hughes et al. (2008), who

⁷Due to data availability for CRSP total returns, portfolio momentum is available starting in portfolio formation year 1983 only. Thus, the models that include portfolio momentum as a variable have 25 fewer observations, one for each portfolio.

Table 5: Regression summary for all portfolios

	Dependent variable: earnings forecast errors												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Investment-to-Assets (I/A)	-0.732** (0.371)			-0.203 (0.425)								-0.439 (0.294)	
Investment Growth (IG)		-0.547** (0.216)		-0.208 (0.212)								-0.056 (0.201)	
Investment-to-Capital (I/K)			-5.900*** (1.655)	-5.378*** (1.394)								-4.936*** (1.078)	-5.040*** (1.381)
Operating Profitability (OP)					2.601** (1.040)			1.962** (0.818)				1.582** (0.683)	1.681*** (0.639)
Gross Profitability (GP)						1.179 (0.827)		0.332 (0.875)				0.399 (0.787)	
Return-on-Equity (ROE)							2.184** (0.931)	1.108** (0.507)				0.742** (0.232)	0.787*** (0.249)
Book-to-Market (log)									1.409** (0.586)			1.243*** (0.414)	1.217*** (0.365)
Market Cap (log)										0.037 (0.107)		0.115 (0.134)	
Portfolio Momentum (12-2)											0.196 (0.539)	-0.046 (0.319)	
F Statistic	39.86	40.67	43.47	42.23	43.2	39.74	42.09	42.25	42.6	39.43	39.85	44.23	47.65
p-value (F Statistic)	0	0	0	0	0	0	0	0	0	0	0	0	0
Portfolio-Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	875	875	875	875	875	875	875	875	875	875	875	875	875
R ²	0.743	0.746	0.759	0.760	0.758	0.742	0.753	0.760	0.755	0.741	0.745	0.789	0.784
Adjusted R ²	0.724	0.728	0.741	0.742	0.740	0.723	0.735	0.742	0.737	0.722	0.726	0.771	0.768
Residual Std. Error	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006

Note: * p<0.1; ** p<0.05; *** p<0.01
This table shows the estimated coefficients in panel regressions of earnings forecast errors for 25 portfolios formed on size and the book-to-market ratio on corporate fundamentals for the 35 portfolio formation years from 1982-2016. Earnings forecast errors in year t are defined as a firms' actual trailing 12 month earnings per share measured in June t+1 minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t. Investment-to-Assets (I/A) is defined as the annual change in total assets (Compustat annual item AT) divided by one-year lagged total assets. Investment growth (IG) in the portfolio formation year t is the growth rate in capital expenditures (Compustat annual item CAPX) from the fiscal year ending in calendar year t-2 to the fiscal year ending in t-1. Investment-to-Capital (I/K) is defined as capital expenditures (Compustat data item CAPX) divided by the net book value of property, plant, and equipment (data item PPENT). Operating profitability (OP) in the sort for June of year t is measured with accounting data for the fiscal year ending in year t-1 and is defined as revenues minus cost of good sold, minus selling, general, and administrative expenses, minus interest expense all divided by the book value of equity. It requires non-missing data for at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expense. Gross Profitability (GP) is defined as revenues (REV) minus cost of goods sold (COGS) scaled by total assets (AT). Return-on-Equity (ROE) is income before extraordinary items (Compustat annual item IB) divided by the lagged book value of equity. Earnings forecast errors as well as all corporate fundamentals are weighted by market capitalization within each portfolio. In addition, earnings forecast errors and all investment- and profitability-based measures are trimmed every year at the 1 percent and 99 percent levels. Standard errors (in parentheses) are double-clustered at the portfolio and time dimension.

also document a negative coefficient for the two investment-related measures they employ (changes of property, plant and equipment, and other long-term assets in the previous year). Models (5)-(7) illustrate the effect for each of the three profitability-based measures when employed individually. The coefficients are positive for all three measures and significant at the 5% level for Operating Profitability and Return-on-Equity but not for Gross Profitability. When we employ all three profitability-related variables combined in model (8), the coefficients for both Operating Profitability and Return-on-Equity remain highly significant ($p < 0.05$). However, the magnitude of the coefficient for Return-on-Equity reduces in half, whereas the coefficient for Operating Profitability remains relatively stable at approximately -2. Thus, higher profitability in the form of higher Operating Profitability and Return-on-Equity leads to improved earnings forecast errors, which can be the result of higher actual earnings in the next period, lower estimated earnings for the next period, or a combination thereof.

Model (9) shows the effect of the natural log of the book-to-market ratio on earnings forecast errors. The positive coefficient, which is significant at the 5% level, implies that a higher book-to-market ratio (i.e., a cheaper valuation) leads to higher earnings forecast errors, which can be the result of either greater actual earnings in the next period, lower estimated earnings for the next period, or a combination thereof. The coefficients for both the log of the market capitalisation and portfolio momentum (12-2 month) are insignificant. The positive relationship between the book-to-market ratio and earnings forecast errors is also reported by So (2013). However, So (2013) and Hughes et al. (2008) reported a significantly positive coefficient for momentum and size. This might be because our results are based on portfolio-level data while So (2013) and Hughes et al. (2008) used firm-level data. When we combine all nine tested corporate fundamentals in model (12) (the “kitchen sink model”) Investment-to-Capital and the log of the book-to-market ratio remain highly significant but with a slightly reduced coefficient for Investment-to-Capital compared to when regressed individually. The two significant measures of profitability, Operating Profitability and Return-

on-Equity, also remain highly significant in the kitchen sink model, albeit with reduced coefficients compared to when regressed alone. Finally, we include in model (13) only the four significant variables from the kitchen sink model (12) and thus reduce the noise from insignificant corporate fundamentals. A comparison of models (12) and (13) confirms the stability and significance of the coefficients: Investment-to-Capital has a negative effect on earnings forecast errors while Operating Profitability, Return-on-Equity, and the log of the book-to-market ratio have a positive effect.

Table 6 illustrates the regression summary for the 10 value portfolios, and Table 7 carries the regression results for the 10 growth portfolios as defined in Section 2.3.2. Starting with the three investment-related measures, the coefficients for all three measures are negative across the growth portfolios. However, only the coefficient for Investment-to-Capital is significant at the 5% level when regressed individually. When all three investment-based measures are combined in model (4), Investment-to-Capital remains the only significant variable, similar to the results for all 25 portfolios. Looking at the results for the 10 value portfolios, Investment-to-Capital is the only significant variable both when regressed alone (model (3)) as well as when combined with the other investment measures (model (4)). However, the magnitude of the coefficient is only about half the size compared to the results for the growth portfolios. Thus, it seems that corporate investments, especially measured via the Investment-to-Capital ratio, have a stronger effect on earnings forecast errors for growth firms than for value firms. Looking at the three measures of profitability, the results for the growth portfolios largely mirror the results for all 25 portfolios: The coefficient for both Operating Profitability and Return-on-Equity is positive and significant at the 5% level when regressed individually. When all three profitability-related measures are combined in model (8), only Return-on-Equity remains significant at the 5% level, albeit with a substantially lower coefficient. The coefficient for Gross Profitability, while also positive, is insignificant.

However, the results for the value portfolios reveal a different picture. When regressed

individually, only Return-on-Equity is significant (at the 5% level). Surprisingly, the coefficient for Gross Profitability turns negative but is statistically insignificant. Interestingly, when all three investment-related measures are combined, the coefficient for Return-on-Equity becomes even more significant ($p < 0.01$), and the negative coefficient for Gross Profitability becomes significant as well (at the 10% level).

Looking at the last group of corporate fundamentals, while the book-to-market ratio is significant across all 25 portfolios, it is insignificant for the two sub-groups containing growth as well as value portfolios. The log of the market capitalisation is significantly positively related to earnings forecast errors only for growth portfolios. Portfolio momentum is not significant for value and growth portfolios as it was for all 25 portfolios. When combining all tested variables in the kitchen-sink model (12), the results are slightly different for growth and value portfolios: For growth stocks, most of the corporate fundamentals that are significant when regressed individually remain significant (Operating Profitability, Return-on-Equity, and market capitalisation). The exception is that none of the investment-related variables (Investment Growth and Investment-to-Capital) remain significant. For value stocks, Investment-to-Capital remains significant with a relatively stable coefficient of approximately -3. Among the three profitability measures, Return-on-Equity remains significant in the kitchen-sink model at the 5% level with a slightly lower magnitude in the coefficient. Interestingly, market capitalisation becomes weakly significant for value stocks when combined with other corporate fundamentals, but the coefficient is only half the size of that for growth stocks. Neither the book-to-market ratio nor portfolio momentum seem to be important in predicting earnings forecast errors for value stocks.

Lastly, when we combine only the four variables that are significant across all 25 portfolios in model (13) - namely Investment-to-Capital, Operating Profitability, Return-on-Equity, and the book-to-market ratio - the results for growth and value stocks become more aligned again. Both groups of stocks have a significantly negative coefficient for Investment-to-Capital with a

Table 6: Regression summary for 10 value portfolios

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	earnings forecast errors												
Investment-to-Assets (I/A)	-0.080 (0.414)			0.105 (0.408)								0.020 (0.357)	
Investment Growth (IG)		-0.289 (0.187)		-0.182 (0.211)								-0.136 (0.209)	
Investment-to-Capital (I/K)			-3.061*** (1.180)	-2.852** (1.135)								-2.779** (1.091)	-3.312*** (1.131)
Operating Profitability (OP)					0.449 (0.821)			1.055 (0.880)				0.614 (1.151)	0.761 (0.931)
Gross Profitability (GP)						-0.940 (0.597)		-1.479** (0.724)				-0.514 (0.920)	
Return-on-Equity (ROE)							0.629** (0.264)	0.583*** (0.207)				0.403** (0.184)	0.727
Book-to-Market (log)									0.697 (0.546)			0.913* (0.549)	0.541 (0.579)
Market Cap (log)										0.138 (0.118)		0.186* (0.102)	
Portfolio Momentum (12-2)											0.223 (0.224)	0.136 (0.227)	
F Statistic	14.7	14.93	15.74	15.04	14.72	14.83	14.78	14.29	14.9	14.8	15.67	14.38	14.98
p-value (F-Statistic)	0	0	0	0	0	0	0	0	0	0	0	0	0
Portfolio-Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	350	350	350	350	350	350	350	350	350	350	340	340	350
Adjusted R ²	0.633	0.637	0.650	0.649	0.634	0.636	0.635	0.637	0.637	0.635	0.650	0.668	0.653

Note: This table shows the estimated coefficients in panel regressions of earnings forecast errors for the 10 value portfolios out of the 25 portfolios formed on size and the book-to-market ratio on corporate fundamentals for the 35 portfolio formation years from 1982-2016. Earnings forecast errors in year t are defined as a firms' actual trailing 12 month earnings per share measured in June t+1 minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t. Investment-to-Assets (I/A) is defined as the annual change in total assets (Compustat annual item AT) divided by one-year lagged total assets. Investment growth (IG) in the portfolio formation year t is the growth rate in capital expenditures (Compustat annual item CAPX) from the fiscal year ending in calendar year t-2 to the fiscal year ending in t-1. Investment-to-Capital (I/K) is defined as capital expenditures (Compustat data item CAPX) divided by the net book value of property, plant, and equipment (data item PPE). Operating profitability (OP) in the sort for June of year t is measured with accounting data for the fiscal year ending in year t-1 and is defined as revenues minus cost of good sold, minus selling, general, and administrative expenses, minus interest expense all divided by the book value of equity. It requires non-missing data for at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expense. Gross Profitability (GP) is defined as revenues (REV.T) minus cost of goods sold (COGS) scaled by total assets (AT). Return-on-Equity (ROE) is income before extraordinary items (Compustat annual item IB) divided by the lagged book value of equity. Earnings forecast errors as well as all corporate fundamentals are weighted by market capitalization within each portfolio. In addition, earnings forecast errors and all investment- and profitability-based measures are trimmed every year at the 1 percent and 99 percent levels. Standard errors (in parentheses) are double-clustered at the portfolio and time dimension.

* p<0.1; ** p<0.05; *** p<0.01

Table 7: Regression summary for 10 growth portfolios

	Dependent variable:												
	earnings forecast errors												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Investment-to-Assets (I/A)	-1.159 (0.800)			-0.262 (1.050)								-0.837 (0.804)	
Investment Growth (IG)		-0.563* (0.325)		-0.229 (0.297)								-0.096 (0.235)	
Investment-to-Capital (I/K)			-5.987** (2.414)	-4.994*** (1.830)								-3.195* (1.835)	-4.403** (2.105)
Operating Profitability (OP)					1.931** (0.878)			1.275* (0.742)				1.079** (0.449)	1.072*** (0.389)
Gross Profitability (GP)						0.684 (1.439)		0.103 (1.493)				0.238 (1.413)	
Return-on-Equity (ROE)							1.978** (0.793)	1.146** (0.539)				0.885*** (0.250)	0.971*** (0.283)
Book-to-Market (log)									0.623 (0.943)			0.553 (0.607)	0.478 (0.675)
Market Cap (log)										0.448** (0.204)		0.392* (0.218)	
Portfolio Momentum (12-2)											0.242 (0.907)	-0.280 (0.431)	

Note: This table shows the estimated coefficients in panel regressions of earnings forecast errors for the 10 growth portfolios out of the 25 portfolios formed on size and the book-to-market ratio on corporate fundamentals for the 35 portfolio formation years from 1982-2016. Earnings forecast errors in year t are defined as a firms' actual trailing 12 month earnings per share measured in June $t+1$ minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t . Investment-to-Assets (I/A) is defined as the annual change in total assets (Compustat annual item AT) divided by one-year lagged total assets. Investment growth (IG) in the portfolio formation year t is the growth rate in capital expenditures (Compustat annual item CAPX) from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in $t-1$. Investment-to-Capital (I/K) is defined as capital expenditures (Compustat data item CAPX) divided by the net book value of property, plant, and equipment (data item PPENT). Operating profitability (OP) in the sort for June of year t is measured with accounting data for the fiscal year ending in year $t-1$ and is defined as revenues minus cost of good sold, minus selling, general, and administrative expenses, minus interest expense all divided by the book value of equity. It requires non-missing data for at least one of the following: cost of goods sold, selling, general and administrative expenses, or interest expense. Gross Profitability (GP) is defined as revenues (REVT) minus cost of goods sold (COGS) scaled by total assets (AT). Return-on-Equity (ROE) is income before extraordinary items (Compustat annual item IB) divided by the lagged book value of equity. Earnings forecast errors as well as all corporate fundamentals are weighted by market capitalization within each portfolio. In addition, earnings forecast errors and all investment- and profitability-based measures are trimmed every year at the 1 percent and 99 percent levels. Standard errors (in parentheses) are double-clustered at the portfolio and time dimension.

* p<0.1; ** p<0.05; *** p<0.01

slightly higher magnitude for growth stocks. Both value and growth stocks also have a positive relationship between Operating Profitability and earnings forecast errors, but the coefficient is significant only for growth stocks ($p < 0.01$). Return-on-Equity is significant for both group of stocks, with a positive coefficient of approximately 1. Lastly, the book-to-market ratio has an insignificant coefficient of only approximately 0.5 for both value and growth stocks, as opposed to a significant coefficient of approximately 1.2 for all 25 portfolios.

Overall, the adjusted R^2 measures for growth portfolios range between 0.77 and 0.79 for all 13 tested models while they range between 0.63 and 0.67 for the value portfolios. The adjusted R^2 measure for all 25 portfolios combined lies between 0.72 and 0.77. Thus, the tested corporate fundamentals explain a much higher variance in earnings forecast errors for growth stocks compared to value stocks.

2.5 Chapter Conclusion

In this paper, we examine how firm characteristics contribute to the empirical finding that analyst earnings forecasts are overly optimistic. We focus on firm characteristics that underlie popular risk-factor models with a focus on investment and profitability measures, as they are the main drivers of the cross-section of expected returns (Hou et al., 2017).

Overall, our results emphasise the role of information uncertainty when estimating the value of a firm. According to Zhang (2006) information uncertainty can potentially stem from two sources: volatility of a firm's underlying fundamentals and poor information. Based on this, he argues that high-uncertainty stocks are likely to be growth stocks. Furthermore, since small firms have less information available to the market, he uses firm size as one proxy for information uncertainty. In line with that, we find that growth stocks, and to a lesser extent, small-cap stocks have a higher volatility in their investment and profitability measures along with more volatile returns. Additionally, we demonstrate that small-growth stocks have the most negative and most volatile earnings forecast errors.

We also demonstrate that measures of corporate investments are negatively related to future earnings forecast errors. This implies that higher investments (specifically measured via Investment-to-Capital) lead to either lower actual earnings in the next period, higher estimated earnings for the next period, or a combination of the two. Higher profitability, measured as Operating Profitability and Return-on-Equity, has the opposite effect and leads to improved earnings forecast errors. The book-to-market ratio also has a significant positive effect on earnings forecast errors, which implies that a higher book-to-market ratio (i.e., a cheaper valuation) is related to improved earnings forecast errors, which can be the result of either higher actual earnings in the next period or lower estimated earnings for the next period. When separately comparing the results for portfolios of value and growth stocks, the direction of the relationship is largely the same for both type of stocks. However, the magnitude of the coefficients is more pronounced for growth stocks, and the tested corporate fundamentals explain a much higher variance in earnings forecast errors for growth stocks compared to value stocks. Again, this emphasises the greater role of information uncertainty for growth stocks.

This study contributes to the finance literature in several ways. First, to our best knowledge, this is the first study that directly links the properties of earnings forecast errors to corporate fundamentals underlying the risk factors in the most important models explaining the cross-section of stock returns. Second, our findings provide further evidence on the role of information uncertainty, potentially caused by volatility in a firm's underlying fundamentals and poor information, in evaluating a the company's value in light of new information. Finally, the presented evidence also provides new insights into the underlying cause of the value effect. Our results suggest that mispricing in the form of earnings forecast errors should be taken into account when analysing the value effect.

Future research might expand the set of company characteristics. We focused on nine characteristics that underlie popular risk-factor models. Studies such as those by Green et al. (2017)

provide a comprehensive overview of the characteristics that provide independent information about U.S. stock returns. Follow-up studies can analyse to what extent these characteristics also provide additional explanatory power for earnings forecast errors. Furthermore, earnings forecast errors are measured at an annual frequency in our study, which limits the number of observations in our sample substantially. Follow-up studies might examine earnings forecast errors over various forecast horizons (other than 12 months) and at a higher frequency. The limitation is that mispricing, in the form of earnings forecast errors, needs some time to materialize in order to be measurable.

3 Earnings Forecast Errors and Risk-Factor Models⁸

3.1 Chapter Introduction

There is substantial evidence that stock market anomalies, in part, reflect forms of mispricing and that stocks share similar components of mispricing. This point is highlighted, for example, by Hirshleifer & Jiang (2010), who use an equity and debt financing-based misvaluation factor, and Kozak et al. (2018), who argue that sentiment-investor demand may result in substantial mispricing. As noted by Stambaugh & Yuan (2017), factor models can be useful to examine whether expected returns reflect some sort of risk or mispricing. The factors may capture systematic risk where investors demand a risk premium as compensation for bearing that risk. Likewise, factors can capture sources of mispricing such as investor sentiment or uncertainty regarding earnings. In this paper we examine how uncertainty about those earnings as measured by earnings forecast errors contributes to the mispricing phenomenon. Earnings forecast errors have been put forward as a mispricing-based explanation of the value premium (Piotroski & So (2012)) and have the advantage of being a non-return-based measure. Therefore, this allows for a direct analysis of expectation errors caused by institutional investors and analysts.

Our study is motivated by three results from the empirical finance literature. First, studies such as those by Hou et al. (2017) and Fama & French (2016) have demonstrated that popular risk factor models - the Fama & French (2015) five-factor model, the Carhart (1997) four-factor model, and the Hou et al. (2015) q -factor model - largely summarise the cross-section of average stock returns. Second, Hirshleifer & Jiang (2010), Stambaugh & Yuan (2017), and others have found that many return-anomaly studies reveal that some form of mispricing is at least partially responsible for the reported anomaly returns. Based on this, Stambaugh & Yuan (2017) have found that their four-factor model with two mispricing factors

⁸unpublished working paper

accommodates a large set of return anomalies even better than the aforementioned four- and five-factor models. Third, and relatedly, Piotroski & So (2012) provide a mispricing-based explanation of the well-documented outperformance of value stocks over growth stocks (known as the value premium). They document that the value/glamour returns and *ex post* revisions to market expectations such as earnings forecast errors are predictably concentrated among firms with *ex ante* biased market expectations. This study combines these three ideas and tests, first, the extent to which earnings forecast errors as a specific proxy for mispricing are a priced factor when added to well-documented risk-factor models. Second, we examine whether the presence of earnings forecast errors affects the estimated risk premia of existing risk factors. Here, we also test whether earnings forecast errors capture different aspects of mispricing other than the two comprehensive mispricing factors applied in the Stambaugh & Yuan (2017) four-factor model. Third, we assess whether augmenting popular risk-factor models with earnings forecast errors as an additional factor raises their already very high explanatory power for stock returns.

Every year, we assign stocks into 25 portfolios based on their book-to-market ratio and firm size. Using data for the 34 portfolio formation years 1982–2015, we find in time series regressions consistent results across the four tested models. When significant, the coefficient for earnings forecast errors is always strongly positive, which is the case for most of the portfolios carrying larger companies. This implies that less mispricing in the form of less negative earnings forecast errors corresponds to higher contemporaneous returns. Additionally, the coefficient for earnings forecast errors is, on average, five times higher for value stocks compared to growth stocks. Adding earnings forecast errors as a proxy for mispricing lowers the estimated betas of the market excess return and the value risk factor (HML) for value stocks in all tested models. Therefore, some of the perceived general stock market risk and the value premium for value stocks might instead be uncertainty regarding earnings as measured by earnings forecast errors. Conversely, adding earnings forecast errors has the

effect of raising the estimated profitability risk premium (RMW). Additionally, we find that in the Stambaugh & Yuan (2017) four-factor model with two mispricing factors, earnings forecast errors pick up some of the negative risk premium for growth stocks for the mispricing factor “MGMT”, which captures mispricing related to the six anomaly variables that a firm’s management can affect rather directly. More importantly, the coefficient for earnings forecast errors is significant for 18 of the 25 portfolios when added to the Stambaugh & Yuan (2017) four-factor model. It is thus the most significant mispricing factor, by far, among the three included. This indicates that earnings forecasts errors are, on the one hand, related to existing mispricing factors in the literature but, on the other hand, also capture with uncertainty regarding earnings a distinctively different mispricing aspect. Overall, adding earnings forecast errors significantly raises the portion of variability explained in the returns of the 25 size- and book-to-market-sorted portfolios as measured by the adjusted R^2 in all four tested models. This effect is more pronounced for portfolios of large-cap and value stocks where the more complex model, including earnings forecast errors, is significantly better at explaining portfolio returns as documented in related *F-tests*.

This study contributes to the finance literature in several ways. First, to our best knowledge, this is the first study that tests the explanatory power of earnings forecast errors for the cross-section of average portfolio returns in the presence of popular risk factors. This paper provides evidence supporting the hypothesis that both risk factors and mispricing in the form of earnings forecast errors are significant drivers in the cross-section of stock returns. The fact that earnings forecast errors carry a positive premium suggests that less mispricing in the form of less negative earnings forecast errors is rewarded with higher contemporaneous returns. We find that this effect is more pronounced for large-cap stocks. Second, the evidence presented here sheds new light on the role of earnings forecast errors in the mispricing literature. In prior literature, mispricing is often modelled based on accounting- and performance-related variables (Stambaugh & Yuan (2017)) or corporate finance-based variables (Hirshleifer &

Jiang (2010)). We demonstrate that earnings forecasts errors capture with uncertainty regarding earnings a different dimension of mispricing.

The remainder of this paper is organised as follows: The next section discusses the related literature, while Section 3.3 describes the sample data, the measurement of earnings forecast errors, and the methodology. Section 3.4 provides the empirical results of our estimated time series regressions, and Section 3.5 concludes.

3.2 Literature Review

One of the first studies that analysed the predictive power of analyst forecasts for cross-sectional returns was by Frankel & Lee (1998). They analysed the predictability of future analyst forecast errors to identify potential mispricing. They demonstrated that cross-sectional errors in three-year-ahead I/B/E/S⁹ consensus earnings forecasts are predictable based on firm characteristics, including the book-to-price ratio, sales growth, and analysts' long-term growth forecasts. Combining these variables in a prediction model, Frankel & Lee (1998) found that the predicted error in long-term forecasts has, in turn, predictive power for cross-sectional returns incremental to an analyst-based residual income model plus company size and market beta.

Hughes et al. (2008) investigated the relationship between predictable market returns and predictable analyst forecast errors. They also found that analyst forecast errors are predictable and that the predictable component of abnormal returns is significantly related to subsequent forecast errors. However, trading strategies that sort firms by predicted forecast errors do not produce abnormal returns. Thus, the authors concluded that investors do not overweight analyst forecasts and that market prices efficiently reflect the predictable component of analyst forecast errors. In a related study, So (2013) reported conflicting results: He used

⁹I/B/E/S, the Institutional Brokers' Estimate System, is a database from Refinitiv. It is an historical earnings estimate database containing analyst estimates for more than 20 forecast measures - including earnings per share, revenue, price targets, EBITDA and pre-tax profits - covering both U.S. and international companies.

firm characteristics to predict future earnings and found that the difference between these characteristic forecasts and analyst earnings estimates had significant predictive power for both analyst forecast errors and forward returns. Specifically, he found that companies where the characteristic forecast exceeded the analyst forecast tended to have realised earnings coming in higher than the consensus analyst forecast (and vice versa). Subsequently, analysts slowly revised their earnings forecasts in the direction of the characteristic forecasts. Based on this, So (2013) concluded that investors' overreliance on analyst forecasts is likely to cause valuation errors that lead to mispricing. In a further analysis, So (2013) confirmed the findings of Hughes et al. (2008), which predicted that forecast errors are not a robust predictor of future returns in cross-sectional tests. In a related study, Dechow & Sloan (1997) assessed the ability of naive investor expectation models to explain the returns to contrarian investment strategies. They found that stock prices naively reflected overly optimistic analyst forecasts of long-term earnings growth, which can explain more than half of the returns to contrarian investment strategies.

Da & Warachka (2009) analysed the systematic risk attributable to fluctuations in expected cashflows. Specifically, their cashflow risk measure was based on analyst forecast revisions and was measured as co-movement between changes in portfolio-level expected cashflow and changes in the market's expected cashflow (the so-called "earnings beta"). They found that these earnings betas were higher for value stocks, small stocks, and past long-term losers compared to growth stocks, large stocks, and past long-term winners. Overall, the measured earnings betas explained more than 55% of the contemporaneous cross-sectional return variation across book-to-market, size, and long-term reversal portfolios. Additionally, the estimated risk premium of cashflow risk was positive, highlighting the importance of analyst forecast revisions.

A study by Piotroski & So (2012) was motivated by the ongoing debate about whether the outperformance of value stocks over growth stocks represents compensation for risk or is a

form of mispricing and highlights the role of expectation errors in that context. Specifically, they argued that expectations embedded in different valuation multiples of value and growth stocks need to be analysed in relation to the strength of a company's fundamentals: Firms with high or low pricing multiples are mispriced only if their stock prices are not warranted given the strength of the firms' fundamentals (Piotroski & So (2012), p. 2869). As part of their analysis, they used two non-return-based measures (consensus forecast errors and revisions in analysts' earnings forecast) to derive expectation errors and expectation adjustments directly from analyst forecasts. Conditioned on a firms' recent financial strength,¹⁰ Piotroski & So (2012) showed that the outperformance of value stocks over growth stocks and *ex post* revisions to market expectations are predictably concentrated among firms with *ex ante* biased market expectations. Based on this, they cast considerable doubt on a risk-based explanation of the value premium.

The literature on risk-factor models begins with the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), which includes only a single market factor. However, over time, more and more violations of the CAPM have been identified. Motivated by these violations, Fama & French (1993) expanded the CAPM to a three-factor model that captures violations related to firm size and value-versus-growth anomalies. In the same year, Jegadeesh & Titman (1993) discovered the momentum effect, which refers to the phenomenon that stocks with high (low) past recent returns are forecasted to have high (low) future returns. The momentum effect is one of the most robust anomalies reported in the asset pricing literature, and Carhart (1997) included it in his four-factor model, along with the market, size, and value factor of Fama & French (1993).

Given the rapid rise in reported return anomalies over the following years, it became clear

¹⁰Piotroski & So (2012) measured the aggregate current strength in firm fundamentals based on nine variables related to profitability, changes in financial leverage and liquidity, and changes in operational efficiency. The nine variables are four profitability-related variables (return-on-assets, cashflow from operations scaled by total assets, change in net income, and accruals scaled by total assets); three variables related to changes in financial leverage & liquidity (change in the ratio of long-term debt to total assets, change in the ratio of current assets to current liabilities, and common equity issuance); and two operating efficiency-related variables (change in gross margin and change in the asset turnover ratio).

that additional factors are needed that are better able to capture the documented anomalies. Two factors among many proposed in the literature received significant attention: Based on an investment-based pricing model, Hou et al. (2015) proposed a four-factor model (the q -factor model) covering the known market and size factor plus two new factors based on investment and profitability. Motivated by the dividend discount valuation model, Fama & French (2015) also added related but different versions of the investment and profitability factors to their three-factor model (Fama & French (1993)), thus creating a five-factor model. In a follow-up study, Fama & French (2016) demonstrated the ability of their five-factor model to substantially shrink the list of anomalies, in part because the factor exposures of many anomalies reveal that they are largely the same phenomenon. Hou et al. (2017) tested in their follow-up study the ability of the most prominent factor models in explaining 216 reported significant anomalies between 1967 and 2014. The tested models include the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965); the Fama & French (1993) three-factor model; the Carhart (1997) four-factor model; the Pástor & Stambaugh (2003) four-factor model, which includes a liquidity factor; the Fama & French (2015) five-factor model; and their own Hou et al. (2015) q -factor model. They find that the q -factor model performs best in explaining anomalies related to momentum and profitability, while the Fama & French (2015) five-factor model outperforms slightly in explaining value-versus-growth anomalies. Overall, they concluded that corporate fundamentals such as investment and profitability, but not liquidity, are the main drivers of the cross-section of expected returns. Stambaugh & Yuan (2017) found that many return-anomaly studies reveal that some sort of mispricing is at least partially responsible for the reported anomaly returns. Based on this, Stambaugh & Yuan (2017) took a different approach in constructing anomaly factors: Instead of having each factor related to one specific anomaly, they constructed two factors based on a stock's average rank with respect to 11 mispricing anomalies that were analysed by Stambaugh, Yu, & Yuan (2012); Stambaugh, Yu, & Yuan (2014); and Stambaugh, Yu,

& Yuan (2015).¹¹ Interestingly, none of the 11 mispricing anomalies were related to analyst forecasts and analyst forecast errors. When combining the two mispricing factors along with the market and a size factor to a four-factor model, they found that the model was better able to explain a large set of anomalies than both the Hou et al. (2015) q -factor model and the Fama & French (2015) five-factor model. Additionally, the model of Stambaugh & Yuan (2017) was reported to be superior in relation to the ability to explain each other’s factor returns.

3.3 Data and Methodology

3.3.1 Risk Factors

The sample data comes from multiple sources. Monthly returns for the six risk factors of market excess return (MKT-RF), size (SMB), value (HML), profitability (RMW), investment (CMW), and momentum (MOM) are from Kenneth R. French’s website.¹² The market factor is the excess return on the market calculated as the value-weighted return of all CRSP firms incorporated in the United States and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 (NYSE common excluding foreign, ADRs, REIT, and closed-end funds) or 11 (NYSE/NYSE American common excluding foreign, ADRs, REIT, closed-end funds) at the beginning of month t , valid shares and price data at the beginning of t , and valid return data for t minus the one-month Treasury bill rate, which is from Ibbotson Associates. For the construction of the size (SMB), value (HML), profitability (RMW), and investment (CMW) factors, Fama & French (2015) use the six value-weighted portfolios formed on size and the book-to-market ratio, the six value-weighted portfolios formed on size and operating

¹¹Stambaugh & Yuan (2017) average the ranking within two clusters whose long-short returns have the highest correlations. The first cluster of anomalies is composed of net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment to assets. These anomaly variables can be rather directly influenced by the company’s management, thus, Stambaugh & Yuan (2017) label this factor “Management (MGMT)”. The second cluster includes distress, O-score, momentum, gross profitability, and return on assets. Since these variables are more performance-related, the factor is labelled “Performance (PERF)”.

¹²http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5_factors_2x3.html

profitability, and the six value-weighted portfolios formed on size and investment (18 portfolios in total). These portfolios are constructed by sorting stocks in a region into two size and three respective book-to-market (B/M), operating profitability (OP), and investment (INV) groups.¹³ In a next step, Fama & French (2015) define the size factor SMB (Small Minus Big) as the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios:

$$SMB_{B/M} = \frac{1}{3}(Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3}(Big\ Value + Big\ Neutral + Big\ Growth)$$

$$SMB_{OP} = \frac{1}{3}(Small\ Robust + Small\ Neutral + Small\ Weak) - \frac{1}{3}(Big\ Robust + Big\ Neutral + Big\ Weak)$$

$$SMB_{INV} = \frac{1}{3}(Small\ Conservative + Small\ Neutral + Small\ Aggressive) - \frac{1}{3}(Big\ Conservative + Big\ Neutral + Big\ Aggressive)$$

$$SMB = \frac{1}{3}(SMB_{B/M} + SMB_{OP} + SMB_{INV})$$

The value factor HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios:

$$HML = \frac{1}{2}(Small\ Value + Big\ Value) - \frac{1}{2}(Small\ Growth + Big\ Growth)$$

¹³For more details on the measurement of the variables, the breakpoints, and the stock universe, see https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/six_portfolios.html, https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/six_portfolios_me_op.html, https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/six_portfolios_me_inv.html.

The profitability factor RMW (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios:

$$RMW = \frac{1}{2}(Small\ Robust + Big\ Robust) - \frac{1}{2}(Small\ Weak + Big\ Weak)$$

The investment factor CMA (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios:

$$CMA = \frac{1}{2}(Small\ Conservative + Big\ Conservative) - \frac{1}{2}(Small\ Aggressive + Big\ Aggressive)$$

A description of the construction of the momentum factor (Mom; WML), which is also briefly described in Fama & French (2012) p. 460, is taken from Kenneth French's website:¹⁴

We use six value-weight portfolios formed on size and prior (2-12 [month]) returns to construct Mom. The portfolios, which are formed monthly, are the intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on prior (2-12) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles. Mom is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios:

$$Mom = \frac{1}{2}(Small\ High + Big\ High) - \frac{1}{2}(Small\ Low + Big\ Low)$$

¹⁴https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html

Table 8: Descriptive statistics for risk factors

Risk Factor	N	Mean	Std. Dev.	Min	Max	ADF	ADF p-value	ADF lag
MKT-RF	34	0.09	0.17	-0.26	0.54	-4.34	0.002	0
SMB	34	0.01	0.09	-0.15	0.23	-3.58	0.012	0
HML	34	0.04	0.15	-0.24	0.6	-6.85	0	1
RMW	34	0.05	0.11	-0.23	0.41	-6.24	0	1
CMA	34	0.04	0.09	-0.07	0.36	-4.49	0.001	1
MOM	34	0.07	0.18	-0.45	0.53	-7.77	0	0
SMBm	34	0.03	0.09	-0.13	0.25	-3.62	0.011	0
MGMT	34	0.08	0.13	-0.17	0.57	-4.79	0.001	0
PERF	34	0.09	0.19	-0.17	0.82	-4.96	0	1

This table shows descriptive statistics for the risk factors for the 34 portfolio formation years from 1982-2015. Risk factor returns are aligned with portfolio returns and calculated from July of year t to June of $t+1$. The market factor MKT-RF is the value-weighted excess return on the market minus the one-month Treasury bill rate. The size and value factors use independent sorts of stocks into two size groups and three book-to-market groups. The size factor, SMB, is the average of the three small stock portfolio returns minus the average of the three big stock portfolio returns. The value factor HML is the average of the two high B/M portfolio returns minus the average of the two low B/M portfolio returns. The profitability factor RMW is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios and the investment factor CMA is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios. The momentum factor is the average return of the two high prior return portfolios minus the average return of the two low prior return portfolios. Data on these risk factors is from Kenneth R. French's website. Data for the two mispricing factors MGMT and PERF and the size factor of Stambaugh (SMBm) is from Robert F. Stambaugh's website. The two mispricing factors are constructed by averaging rankings within two clusters. The first cluster of anomalies includes variables that a firm's management can rather affect directly and are thus labelled as Management (MGMT). The second set of anomalies are more performance-related and thus denoted Performance (PERF). SMBm is the size factor of Stambaugh and Yuan (2017) where they include only stocks that are not used in forming either of the mispricing factors. ADF denote the test statistic, p-value and AIC estimator of the lag length from applying the Augmented Dickey-Fuller test on each risk factor time series. The ADF critical value is -3.43 for the 1 per cent confidence level.

Monthly data for the two mispricing factors are from Robert F. Stambaugh's website.¹⁵ Stambaugh & Yuan (2017) constructed the two mispricing factors by averaging rankings within two clusters among a set of 11 anomalies exhibiting the greatest return co-movement.¹⁶ The first cluster of anomalies included variables that the management of a firm can affect rather directly and were thus labelled as "Management (MGMT)". The second set of anomalies were more performance-related and can be less directly controlled by management. Thus, they were denoted as "Performance (PERF)". The final step in constructing the mispricing factors involved applying a 2x3 sorting procedure that mirrored the approach used by Fama & French (2015) and Hou et al. (2015).¹⁷ Additionally, Stambaugh & Yuan (2017) used their

¹⁵<http://finance.wharton.upenn.edu/~stambaug/>

¹⁶Stambaugh & Yuan (2017) measure similarity by two methods, using either time-series correlations of anomaly returns or average cross-sectional correlations of anomaly rankings. Both methods produce the same two clusters of anomalies; see Stambaugh & Yuan (2017), p. 1277.

¹⁷For more details on the included anomalies and the construction of the mispricing factors, see Stambaugh & Yuan (2017), pp. 1275-1279.

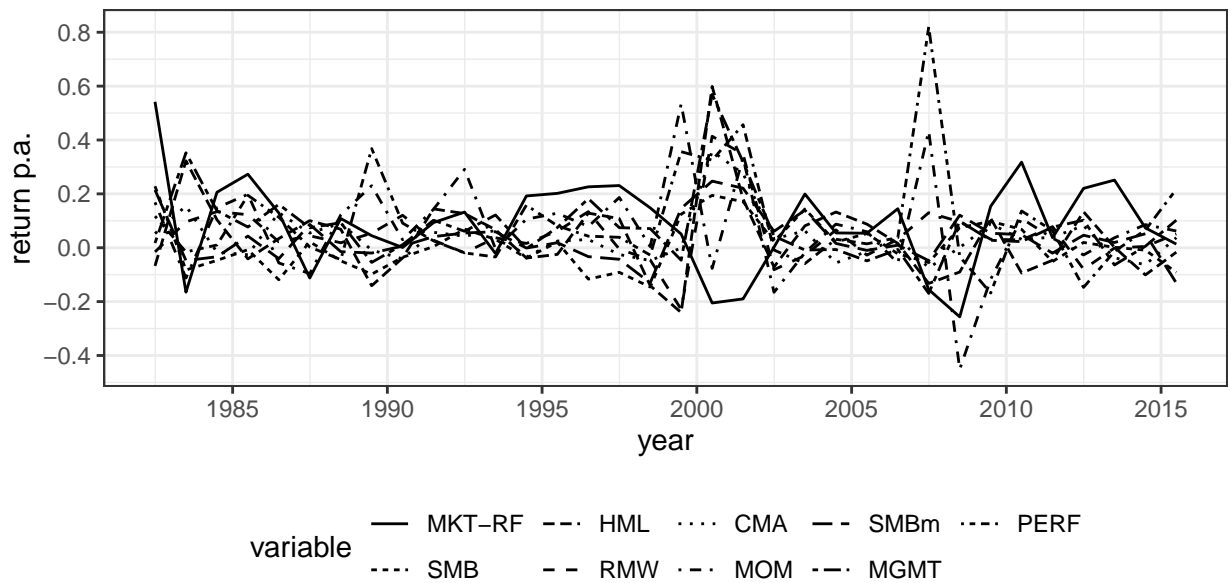
own version of the size factor: They included only stocks that are not used in forming either of the two mispricing factors and are thus less prone to over- and under-pricing. The resulting size factor yielded a size-premium of 46 basis points per month over the 1967-2013 period, almost double the size of the 25 basis points for the SMB factor in the Fama & French (1993) three-factor model. Table 8 confirms that the mean return for the size factor of Stambaugh & Yuan (2017) (SMBm) is also much higher than for the size factor of Fama & French (1993) (SMB) in our sample.

We also evaluate the stationarity of the annual risk factor time series using the augmented Dickey-Fuller (ADF) test with a constant, as all time series have a positive mean (see Table 8). According to Stock & Watson (2015), studies of the ADF statistic suggest that it is better to use the Akaike information criterion (AIC) instead of the Bayes information criterion (BIC) to estimate the lag length for the ADF statistic. The t -values from this test are reported in Table 8 along with the AIC estimator of the lag length. With a critical value of -3.43 at the 1% confidence level, a unit root in all risk factor time series is rejected. Figure 5 has a plot of the annual risk factor time series.

3.3.2 Stock Data

Data on corporate fundamentals is from the CRSP/Compustat merged fundamentals annual and quarterly database. Similar to Xing (2008), Piotroski & So (2012), and Hou et al. (2015), we exclude observations from financial firms (Standard Industrial Classification codes between 6000 and 6999) in our sample. Additionally, we follow Fama & French (2015) and include only ordinary common shares with a CRSP share code 10 (NYSE common excluding foreign, ADRs, REIT, closed-end funds) or 11 (NYSE/NYSE American common excluding foreign, ADRs, REIT, closed-end funds).

Following Fama & French (1993) and Xing (2008), we define the book value of equity (BE) as the Compustat book value of common equity (Compustat annual data item 60) plus



This figure shows the time series of annual returns for risk factors for the 34 portfolio formation years from 1982–2015. Risk factor returns are aligned with portfolio returns and calculated from July of year t to June of $t+1$. The market factor MKT-RF is the value-weighted excess return on the market minus the one-month Treasury bill rate. The size and value factors use independent sorts of stocks into two size groups and three book-to-market groups. The size factor, SMB, is the average of the three small stock portfolio returns minus the average of the three big stock portfolio returns. The value factor HML is the average of the two high B/M portfolio returns minus the average of the two low B/M portfolio returns. The profitability factor RMW is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios and the investment factor CMA is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios. The momentum factor is the average return of the two high prior return portfolios minus the average return of the two low prior return portfolios. Data on these risk factors is from Kenneth R. French's website. Data for the two mispricing factors MGMT and PERF and the size factor of Stambaugh (SMBm) is from Robert F. Stambaugh's website. The two mispricing factors are constructed by averaging rankings within two clusters. The first cluster of anomalies includes variables that a firm's management can rather affect directly and are thus labelled as Management (MGMT). The second set of anomalies are more performance-related and thus denoted Performance (PERF). SMBm is the size factor of Stambaugh & Yuan (2017) where they include only stocks that are not used in forming either of the mispricing factors.

Figure 5: Time series of annual returns for risk factors

balance-sheet deferred taxes (data item 74) and investment tax credits (data item 208), minus the book value of preferred stock. Depending on data availability, we use the redemption (data item 56), liquidation (data item 10), or par value (data item 130) of preferred stock. We follow Xing (2008), Piotroski & So (2012), and Hou et al. (2015) and exclude firms with a negative or zero book value of equity. We categorise firms every year into 25 portfolios based on their book-to-market ratio and firm size. This is a standard approach in asset pricing, which reduces the variability in measures such as earnings forecast errors. Additionally, the classification into portfolios allows for comparisons between value and growth stocks as well as between large caps and small caps. The construction and timing of the 25 size and book-to-market portfolios follows Fama & French (1993), which is also applied by Xing (2008), Fama & French (2015), and Hou et al. (2015). The portfolios are constructed at the end of each June as the intersection of five portfolios formed on firm size (market value of equity, ME) and five portfolios formed on the book-to-market ratio. To construct that ratio, in June of year t , the book value of equity is taken at the end of the fiscal year ending in year $t-1$, and the market value of equity is taken at the end of December of $t-1$. The size breakpoints for year t are the NYSE market equity quintiles at the end of June of t . The BE/ME breakpoints are also based on NYSE quintiles. Since the data for the two mispricing factors from Stambaugh & Yuan (2017) is available until December 2016, the final sample spans the portfolio formation years 1982-2015 and is composed of 50904 firm-year observations.

Stock data is from the CRSP/Compustat merged security monthly database. Monthly excess total returns are calculated as monthly total returns from CRSP minus the total return of the one-month Treasury bill rate, which is downloaded from Kenneth R. French's website.¹⁸ Similar to Fama & French (1993) and Hou et al. (2015), we calculate value-weighted excess portfolio returns from July of year t to June of $t+1$, and the portfolios are rebalanced at the end of June $t+1$.

¹⁸http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

3.3.3 The Measurement of Earnings Forecast Errors

Earnings forecast errors have been put forward as one potential measure of a mispricing-based explanation of the value premium in the literature; see Piotroski & So (2012). The advantage of earnings forecast errors (*EFE*) is that it is a non-return-based measure. Thus, it allows for a direct analysis of expectation errors caused by institutional investors and analysts instead of deriving them indirectly from short-term stock price changes. One restriction is that analyst forecasts are not available for all firms, and the sample will be biased to larger, more profitable firms (Lang & Lundholm, 1996). In our sample, of 122950 firm-year observations with valid corporate fundamental data, 52630 observations (42.81%) also have earnings forecast errors data.

In line with the timing of the portfolio formation, we measure earnings forecast errors every year in June. Following Piotroski & So (2012), we define earnings forecast errors (EFE) in year t for an individual company as the firms' actual trailing 12-month earnings per share measured in June $t+1$, minus consensus 12-month expected earnings per share measured in June t , scaled by total assets per share in year t :

$$EFE_t = \frac{12m \text{ earnings per share}_{t+1} - \text{consensus } 12m \text{ expected earnings per share}_t}{\text{total assets per share}_t}$$

We use shares outstanding from CRSP to calculate total assets per share, which is also used to calculate the market value of equity (ME) in the BE/ME ratio. Thus, for consistency, this measure of shares outstanding is preferred. In a next step, earnings forecast errors are trimmed every year at the 1% and 99% levels to remove the effect of outliers and data errors. In a final step, earnings forecast errors in year t for the 25 size- and book-to-market-sorted portfolios are calculated as the value-weighted average of the earnings forecast errors of all stocks in each portfolio based on the market value of equity (ME) in June of year t for each stock. Research reveals that the accuracy of forecasts deteriorates over longer forecast horizons

(Brown & Mohd, 2003; Clement, 1999; Sinha et al., 1997). Taking this into consideration, we focus on forecasts with a one-year horizon.

Table 9 presents descriptive statistics for the annual excess returns and earnings forecast errors for the 25 size and book-to-market portfolios.¹⁹ It illustrates that value firms have higher annual excess returns than growth firms for every size quintile, except for large firms. This confirms the well-known value effect, i.e. that stocks with high book-to-market ratios have higher average returns than stocks with low book-to-market ratios, which has been identified in many empirical studies (Basu (1977), Fama & French (1992), Xing (2008), Cochrane (2011); amongst others). Moreover, Table 9 confirms the empirical finding that stocks from small companies earn, on average, higher returns than stocks from large firms. This holds for every book-to-market quintile, except for growth stocks, and confirms the empirical finding that the small firm effect did not persist for growth firms after it was first identified by Banz (1981), see Chen & Zhao (2009).

The right panel in Table 9 shows that the mean earnings forecast errors are negative for all portfolios, meaning that analysts' forecasts are, on average, too high, which confirms the findings in prior literature (Dechow & Sloan (1997), Kothari et al. (2016); amongst others). The magnitude of this bias varies by book-to-market ratio and size: Earnings forecast errors are much higher (meaning, more negative) for growth stocks than for value stocks for every size quintile.²⁰ Earnings forecast errors improve almost linearly, going from small to large firms across all book-to-market quintiles, meaning that analyst forecasts on earnings are, on average, more optimistic for small firms compared to large firms. The small-growth portfolio (portfolio 11) has the most negative earnings forecast errors, by far. Dechow & Sloan (1997)

¹⁹The first number for the 25 size and book-to-market portfolios represents the size portfolio: 1x is the small market capitalisation portfolio, 5x is the large market capitalisation portfolio. The second number represents the book-to-market portfolio: x1 is the low book-to-market (growth) portfolio, and x5 is the high low book-to-market (value) portfolio. Thus, portfolio 11 is the small-growth portfolio, and portfolio 55 is the large-value portfolio.

²⁰The last column in Table 4 in Chapter 2.3.2 indicates that the difference in monthly earnings forecast errors between value and growth stocks is statistically significant (at the 5% level) for the smallest three size quintiles but not among large-cap stocks.

also found much higher (i.e., more negative) analyst forecast errors for growth stocks than for value stocks. Piotroski & So (2012) reported analyst forecast errors across growth-, middle-, and value portfolios with no further distinction between firm size. They also found that analyst forecast errors for value stocks marginally exceed those for growth stocks, but the difference is not statistically significant. However, conditioning on the firm's recent financial strength reveals that growth stocks with weak financials produce the largest negative forecast errors, while value firms with strong financials have forecast errors that are only marginally negative.

Similar to the annual risk factor time series, we also evaluate the stationarity of the annual portfolio time series (returns and earnings forecast errors) using the augmented Dickey-Fuller (ADF) test with a constant, since all of the time series have a non-zero mean (see Table 9). The t -statistics from this test are reported in Table 9 along with the AIC estimator of the lag length. With a critical value of -3.43 at the 1% confidence level (5% confidence: -2.86; 10% confidence: -2.57), a unit root in the annual excess return time series for all 25 size and book-to-market portfolios is rejected. A unit root is also rejected for all earnings forecast errors time series at the 1% confidence level except for one portfolio (21), where it is rejected at the 10% level.

3.3.4 Methodology

We estimate multiple regression models with portfolio returns as the dependent variable and combinations of risk factors coupled with earnings forecast errors (*EFE*) as the explanatory variables. We estimate each combination of risk factors based on popular risk-factor models with and without earnings forecast errors (*EFE*) to allow for comparisons of the additional effect of adding earnings forecast errors (*EFE*) to the regression model.

A regular ordinary least squares (OLS) regression has the disadvantage of not considering heterogeneity across groups (portfolios, in our case) or time. However, our data structure is

Table 9: Descriptive statistics for portfolios

Portfolio	annual portfolio excess returns (ret)					earnings forecast errors (EFE)				
	mean (ret)	Std. Dev.(ret)	ADF (ret)	ADF p-value (ret)	ADF lag (ret)	mean (EFE)	Std. Dev.(EFE)	ADF (EFE)	ADF p-value (EFE)	ADF lag (EFE)
11	7.85	27.90	-5.43	0.000	1	-4.03	1.81	-3.48	0.015	0
12	11.25	23.96	-5.26	0.000	0	-2.18	1.01	-3.65	0.010	0
13	12.74	24.46	-5.77	0.000	0	-1.43	0.68	-5.54	0.000	0
14	14.63	25.14	-5.29	0.000	1	-1.26	0.66	-5.98	0.000	0
15	14.95	24.54	-5.26	0.000	1	-0.95	0.68	-5.16	0.000	0
21	7.40	23.02	-5.40	0.000	1	-2.44	1.40	-2.82	0.066	0
22	10.70	19.62	-5.44	0.000	0	-1.19	0.83	-4.20	0.002	0
23	12.58	21.73	-5.51	0.000	1	-0.86	0.67	-5.28	0.000	0
24	9.93	19.28	-5.49	0.000	1	-0.76	0.60	-5.12	0.000	1
25	10.48	23.88	-5.65	0.000	1	-0.75	0.57	-5.83	0.000	0
31	8.07	22.72	-5.93	0.000	1	-1.55	1.46	-4.53	0.001	0
32	11.43	20.99	-5.14	0.000	1	-0.72	0.67	-5.49	0.000	0
33	9.48	19.58	-5.09	0.000	1	-0.74	0.63	-4.80	0.001	0
34	11.82	19.09	-5.49	0.000	1	-0.48	0.64	-5.43	0.000	0
35	14.21	18.30	-5.31	0.000	1	-0.38	0.62	-5.28	0.000	0
41	9.57	19.41	-6.40	0.000	1	-0.82	0.83	-5.08	0.000	1
42	10.32	17.24	-5.69	0.000	1	-0.47	0.61	-5.33	0.000	0
43	9.94	17.45	-5.60	0.000	0	-0.44	0.62	-5.83	0.000	0
44	10.78	19.15	-5.41	0.000	1	-0.44	0.62	-5.73	0.000	0
45	14.27	21.49	-6.01	0.000	1	-0.53	0.95	-4.98	0.000	1
51	10.26	18.80	-4.19	0.003	1	-0.29	0.56	-5.48	0.000	1
52	9.29	17.24	-4.42	0.001	1	-0.18	0.79	-5.93	0.000	0
53	9.14	14.92	-5.18	0.000	0	-0.17	0.66	-6.47	0.000	0
54	9.61	17.51	-5.44	0.000	1	-0.31	0.53	-4.41	0.001	0
55	8.86	20.51	-5.68	0.000	0	-0.20	0.43	-4.58	0.001	0

This table shows annual summary statistics for the 25 portfolios formed on size and book-to-market for the 34 portfolio formation years from 1982-2015. The first number for the portfolios represents the size portfolio: 1x is the small market capitalisation portfolio, 5x is the large market capitalisation portfolio. The second number represents the book-to-market portfolio: x1 is the low book-to-market (growth) portfolio and x5 is the high low book-to-market (value) portfolio. Thus, portfolio 11 is the small-growth portfolio and portfolio 55 is the large-value portfolio. The value-weighted excess portfolio returns are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced at the end of June $t+1$. Value-weighted portfolio earnings forecast errors in the sort for June of year t are defined as firms' actual trailing 12 month earnings per share measured in June $t+1$ minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t . Earnings forecast errors are trimmed every year at the 1% and 99% levels. ADF denote the test statistic, p-value and AIC estimator of the lag length from applying the Augmented Dickey-Fuller test on each risk factor time series. The ADF critical value is -3.43 for the 1 per cent confidence level.

composed of the same risk factor time series for each portfolio, with earnings forecast errors being the only explanatory variable that differs across portfolio and time. Thus, fixed effects are limited in our data set. Additionally, we would like to allow for comparisons between our findings and the results in studies closest to ours, such as Piotroski & So (2012), Fama & French (2015), Hou et al. (2015), and Stambaugh & Yuan (2017), which all estimate regular OLS regressions.

The multiple regression model for the Fama & French (2015) five-factor model including earnings forecast errors is defined as

$$R_{it} - RF_t = \alpha_i + \beta_i MKT - RF_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_i EFE_{it} + u_{it}$$

where $R_{it} - RF_t$ is the excess return of portfolio i over the risk-free rate in time period t , α_i is the intercept of portfolio i , $MKT - RF_t$ is the market excess return in time period t , SMB_t is the return on a diversified portfolio of small stocks minus the return on a diversified

portfolio of big stocks (the size factor, SMB) in time period t , HML_t is the difference between the returns on diversified portfolios of high and low book-to-market stocks (the value factor, HML) in time period t , RMW_t is the difference between the returns on diversified portfolios of stocks with robust and weak profitability (the profitability factor, RMW) in time period t , CMA_t is the difference between the returns on diversified portfolios of the stocks of low and high investment firms (the investment factor, CMA) in time period t , EFE_{it} is the earnings forecast error of portfolio i in time period t , and u_{it} is the error term that is assumed to have a conditional mean of zero.

The Carhart (1997) four-factor model including earnings forecast errors is defined as

$$R_{it} - RF_t = \alpha_i + \beta_i MKT - RF_t + s_i SMB_t + h_i HML_t + w_i WML_t + e_i EFE_{it} + u_{it}$$

where WML_t is the return on a diversified portfolio of past winners minus the return on a diversified portfolio of past losers in time period t . The Hou et al. (2015) q -factor model including earnings forecast errors is defined as

$$R_{it} - RF_t = \alpha_i + \beta_i MKT - RF_t + h_i SMB_t + r_i RMW_t + c_i CMA_t + e_i EFE_{it} + u_{it}$$

Lastly, in a robustness test, we analyse the effect of adding earnings forecast errors to the Stambaugh & Yuan (2017) four-factor model, which includes two mispricing factors in addition to the market and size factor. It is defined as

$$R_{it} - RF_t = \alpha_i + \beta_i MKT - RF_t + sm_i SMBm_t + m_i MGMT_t + p_i PERF_t + e_i EFE_{it} + u_{it}$$

where $SMBm_t$ is the size factor of Stambaugh & Yuan (2017) in time period t , $MGMT_t$ is the first mispricing factor related to variables that a firm's management can affect rather directly, and $PERF_t$ is the second mispricing factor related to a set of more performance-related

anomalies. Test statistics are calculated using Newey & West (1987) standard errors with four lags to account for potential heteroskedasticity and autocorrelation in the standard errors.

3.4 Empirical Results

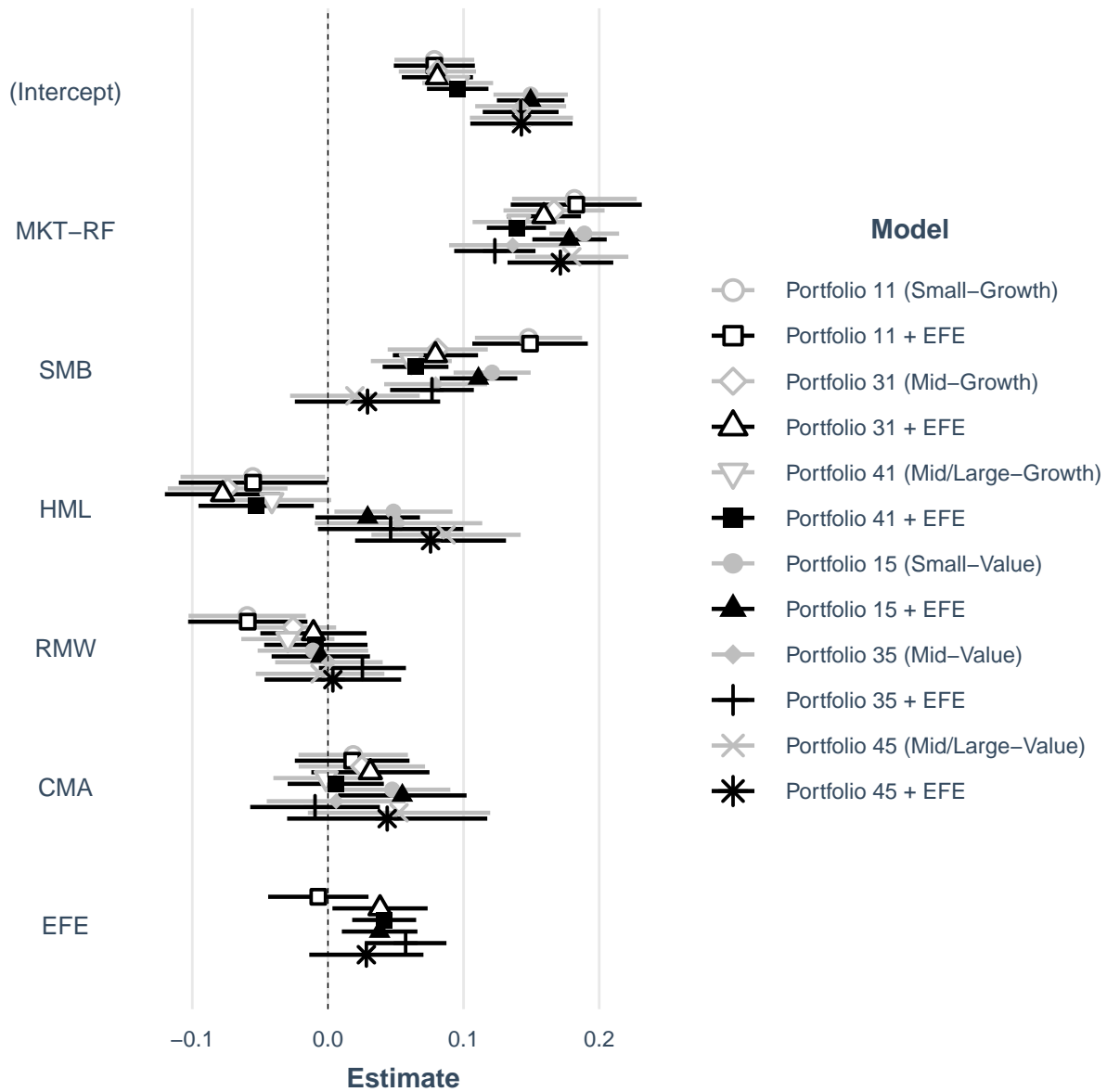
3.4.1 Time Series Regressions

Figures 6-8 illustrate the estimated regression coefficients for the Fama & French (2015) five-factor model, the Carhart (1997) four-factor model, and the Hou et al. (2015) q -factor model. Only a selected number of portfolios is presented to ensure better readability. Furthermore, the predictors are mean-centered and scaled by one standard deviation. Tables 19 to 26 in the appendix present the full regression summary statistics for the three tested models, both in their original composition without earnings forecast errors as well as with earnings forecast errors as an additional explanatory variable.

Adding earnings forecast errors to the three models has little effect on the intercept from the time series regression, which represents the unexplained portion of excess returns. The average mean absolute intercept rises slightly, from 0.02 to 0.03, but remains insignificant for most of the 25 portfolios in each of the tested models. Figures 6-8 illustrate that the intercept tends to be higher for value stocks compared to growth stocks, irrespective of whether earnings forecast errors are added.

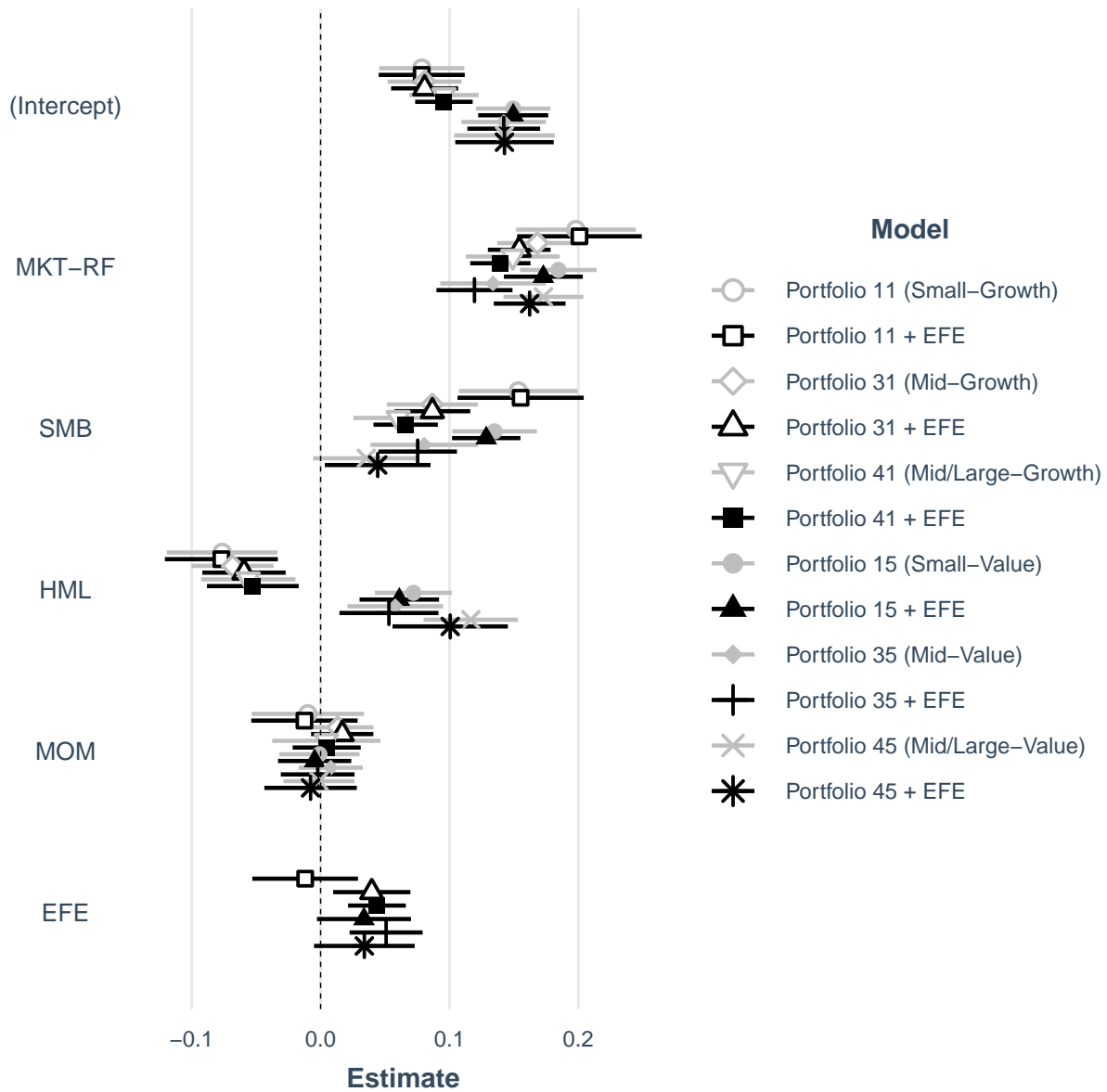
The estimated coefficient for the market excess return (MKT-RF) is reduced by 0.03, on average, across the three tested risk-factor models when earnings forecast errors are added to the equation. Segregating this effect between value and growth stocks further indicates that the estimated market betas for value stocks fall by 0.05, on average, while they remain stable for growth stocks in all three tested models when earnings forecast errors are added. Thus, some of the perceived general stock market risk for value stocks might instead be uncertainty around earnings as measured by earnings forecast errors.

Looking at the exposures to the value risk factor (HML), their average estimated betas are



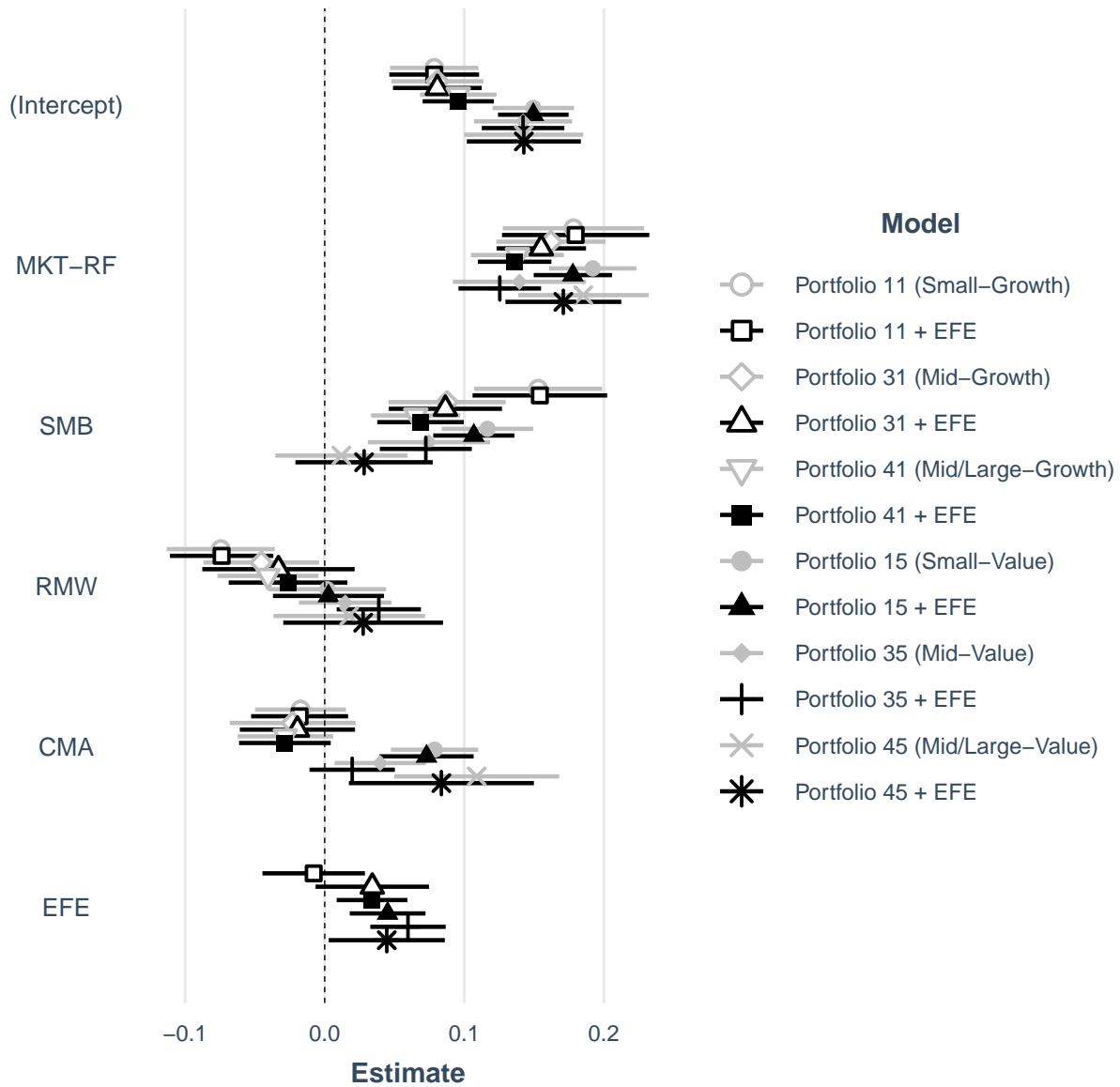
The figure shows regression coefficients of the Fama and French (2015) five-factor model plus earnings forecast errors (EFE) in explaining annual excess returns on a selection of 25 size- and book-to-market sorted portfolios. Due to space limitations the results for only a limited number of portfolios are shown. The Fama and French (2015) five-factor model is comprised of the market excess return (MKT-RF), the size factor (SMB), the value factor (HML), the profitability factor (RMW), and the investment factor (CMA). Value-weighted portfolio earnings forecast errors in the sort for June of year t are defined as firms' actual trailing 12 month earnings per share measured in June $t+1$ minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t . Earnings forecast errors are trimmed every year at the 1% and 99% levels. All predictors are mean-centered and scaled by one standard deviation. The width of the confidence interval is 95% with heteroskedasticity-robust (HC1) standard errors as Newey and West (1987) standard errors are not available here.

Figure 6: Regressions of Fama-French five-factor model and earnings forecast errors



The figure shows regression coefficients of the Carhart (1997) four-factor model plus earnings forecast errors (EFE) in explaining annual excess returns on a selection of 25 size- and book-to-market sorted portfolios. Due to space limitations the results for only a limited number of portfolios are shown. The Carhart (1997) four-factor model is comprised of the market excess return (MKT-RF), the size factor (SMB), the value factor (HML), and the momentum (MOM) factor. Value-weighted portfolio earnings forecast errors in the sort for June of year t are defined as firms' actual trailing 12 month earnings per share measured in June $t+1$ minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t . Earnings forecast errors are trimmed every year at the 1% and 99% levels. All predictors are mean-centered and scaled by one standard deviation. The width of the confidence interval is 95% with heteroskedasticity-robust (HC1) standard errors as Newey and West (1987) standard errors are not available here.

Figure 7: Regressions of Carhart four-factor model and earnings forecast errors



The figure shows regression coefficients of the Hou q-factor model plus earnings forecast errors (EFE) in explaining annual excess returns on a selection of 25 size- and book-to-market sorted portfolios. Due to space limitations the results for only a limited number of portfolios are shown. The Hou q-factor model is comprised of the market excess return (MKT-RF), the size factor (SMB), the profitability factor (RMW), and the investment factor (CMA). Value-weighted portfolio earnings forecast errors in the sort for June of year t are defined as firms' actual trailing 12 month earnings per share measured in June $t+1$ minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t . Earnings forecast errors are trimmed every year at the 1% and 99% levels. All predictors are mean-centered and scaled by one standard deviation. The width of the confidence interval is 95% with heteroskedasticity-robust (HC1) standard errors as Newey and West (1987) standard errors are not available here.

Figure 8: Regressions of Hou q-factor model and earnings forecast errors

stable at approximately -0.38 for growth stocks irrespective of whether earnings forecast errors are added to the equation. Conversely, the estimated HML betas for value stocks are substantially reduced by 0.06, on average, in the presence of earnings forecast errors, both in the Fama & French (2015) five-factor model and the Carhart (1997) four-factor model. Thus, some of the perceived value risk premium might instead be uncertainty regarding earnings as measured by earnings forecast errors.

The exposures to the profitability factor (RMW) tend to be negative for growth portfolios and approximately zero to mildly positive for value portfolios. The RMW coefficient rises, on average, by 0.06 across all portfolios and becomes statistically significant for two more portfolios in both the Fama & French (2015) five-factor model and the Hou et al. (2015) q -factor model when earnings forecast errors are added.

The estimated sensitivities to the investment factor (CMA) varies substantially by risk-factor model: The average estimated betas are mostly insignificant and do not change much in the presence of earnings forecast errors for the Fama & French (2015) five-factor model. However, in the Hou et al. (2015) q -factor model, the average investment betas for the value portfolios (which are predominantly also statistically significant) are substantially lower by 0.11, on average, after the addition of earnings forecast errors as an additional variable. On the other hand, the exposures to the size (SMB) and momentum (WML) factors remain largely unaffected by the addition of earnings forecast errors.

The bottoms of Tables 20, 22, and 24 in the appendix present the coefficients and corresponding standard errors for the earnings forecast errors variable. The coefficient is positive for most of the portfolios and strongly positive when statistically significant, which is the case for 11 respectively 12 portfolios, depending on the model. This implies that less mispricing in the form of less negative earnings forecast errors corresponds to higher contemporaneous returns. A comparison of the results across small- and large-cap portfolios as well as growth and value portfolios reveals that the estimated coefficient for earnings

forecast errors is close to zero and is statistically insignificant for all portfolios in the lowest two size quintiles (portfolios starting with 1 and 2). The only exception is the small-value portfolio (15), which has a significantly positive EFE coefficient in all three tested models. The estimated coefficient for earnings forecast errors is significant for most of the portfolios of larger companies (portfolios starting with 3 and 4), large-cap (portfolios starting with 5), and more value-oriented portfolios (portfolios ending with 4 and 5). This is somewhat surprising, as prior studies, such as Stambaugh & Yuan (2017), found that small-cap stocks, especially, tend to be vulnerable to mispricing. Additionally, the statistical significance of the estimated earnings forecast error coefficient tends to be evenly spread among growth and value portfolios. However, looking at the magnitude, the average coefficient for value portfolios is about five times larger than for growth portfolios.

Table 10 has the adjusted R^2 measure for the estimated regressions without earnings forecast errors (first panel) and with earnings forecast errors included (second panel). The adjusted R^2 lies between 0.68 and 0.93 for the three models without earnings forecast errors and 0.71 and 0.93 with earnings forecast errors included. The only exception is the large-cap value portfolio, which has a substantially lower adjusted R^2 . This confirms the high explanatory power of the three models already documented in prior literature, such as Hou et al. (2017). Comparing the upper two panels illustrates that adding earnings forecast errors as additional variable to the models does not raise the percentage of variation explained for small-cap stocks, but it does so quite substantially for larger-cap stocks, where it raises the adjusted R^2 measure by 2%, on average, on top of the already high values. This is in line with our finding that the coefficient for the earnings forecast errors variable is mainly significant among large-cap portfolios. A comparison of the adjusted R^2 measure for value and growth stocks reveals that adding earnings forecast errors raises the model fit slightly more for value stocks than for growth stocks.

Table 10: Regression statistics

	Fama-French 5 factor					Carhart 4 factor					Hou q-factor				
	Low B/M	2	3	4	High B/M	Low B/M	2	3	4	High B/M	Low B/M	2	3	4	High B/M
<i>adjusted R² without earnings forecast errors</i>															
Small	0.91	0.87	0.88	0.88	0.90	0.89	0.85	0.88	0.89	0.89	0.90	0.87	0.88	0.88	0.88
2	0.82	0.88	0.89	0.91	0.80	0.83	0.89	0.89	0.89	0.80	0.82	0.88	0.90	0.88	0.77
3	0.87	0.93	0.87	0.82	0.73	0.87	0.93	0.88	0.82	0.74	0.83	0.93	0.85	0.79	0.70
4	0.85	0.86	0.81	0.79	0.75	0.84	0.85	0.82	0.78	0.73	0.84	0.86	0.81	0.76	0.68
Big	0.91	0.90	0.84	0.75	0.47	0.90	0.85	0.84	0.70	0.43	0.85	0.90	0.85	0.74	0.34
<i>adjusted R² with earnings forecast errors</i>															
Small	0.91	0.87	0.88	0.87	0.92	0.88	0.85	0.88	0.88	0.90	0.89	0.87	0.87	0.88	0.91
2	0.82	0.88	0.90	0.91	0.80	0.82	0.89	0.89	0.89	0.80	0.81	0.89	0.90	0.88	0.77
3	0.89	0.93	0.89	0.86	0.81	0.89	0.93	0.88	0.84	0.81	0.84	0.93	0.87	0.85	0.79
4	0.89	0.89	0.86	0.81	0.75	0.89	0.86	0.85	0.79	0.74	0.86	0.88	0.85	0.80	0.71
Big	0.91	0.90	0.87	0.81	0.46	0.90	0.84	0.85	0.73	0.44	0.84	0.90	0.87	0.81	0.35
<i>F-statistic</i>															
Small	0.18	0.90	0.33	0.61	18.10	0.38	0.15	0.68	0.26	7.44	0.24	1.43	0.03	0.58	19.35
2	1.30	3.05	1.39	0.88	1.42	0.87	1.97	0.52	0.14	1.28	1.30	3.64	1.26	1.87	2.78
3	8.23	3.39	6.96	30.01	40.76	12.19	1.37	5.72	15.37	30.96	4.83	3.80	7.59	22.69	40.92
4	11.50	41.21	8.98	10.01	4.02	25.29	4.07	8.65	5.63	5.11	5.99	17.72	9.75	12.84	14.49
Big	0.15	2.95	35.48	13.04	0.48	2.48	0.45	20.17	14.41	1.00	0.17	2.20	28.28	10.58	0.86
<i>p-value (F-statistic)</i>															
Small	0.68	0.35	0.57	0.44	0.00	0.54	0.70	0.42	0.61	0.01	0.63	0.24	0.86	0.45	0.00
2	0.26	0.09	0.25	0.36	0.24	0.36	0.17	0.48	0.71	0.27	0.26	0.07	0.27	0.18	0.11
3	0.01	0.08	0.01	0.00	0.00	0.00	0.25	0.02	0.00	0.00	0.04	0.06	0.01	0.00	0.00
4	0.00	0.00	0.01	0.00	0.06	0.00	0.05	0.01	0.02	0.03	0.02	0.00	0.00	0.00	0.00
Big	0.70	0.10	0.00	0.00	0.49	0.13	0.51	0.00	0.00	0.33	0.69	0.15	0.00	0.00	0.36

This table shows in the first two panels the adjusted R² measure of time series regressions of annual portfolio excess returns for 25 portfolios formed on size and the book-to-market ratio on risk-factor models for the 34 portfolio formation years from 1982-2015. Panels three and four show the F-statistic and corresponding p-value of F-tests comparing models with and without earnings forecast errors. The Fama-French 5 factor model is comprised of the market excess return RM-RF, the size factor SMB, the value factor HML, the profitability factor RMW and the investment factor CMA. The Carhart 4 factor model is comprised of the market excess return RM-RF, the size factor SMB, the value factor HML and the momentum factor WML. The Hou q-factor model is comprised of the market excess return RM-RF, the size factor SMB, the profitability factor RMW and the investment factor CMA. Value-weighted portfolio earnings forecast errors in year t are defined as firms' actual trailing 12 month earnings per share measured in June t+1 minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t. Test-statistics are calculated using Newey and West (1987) standard errors with four lags.

The lower two panels report the *F-statistics* and corresponding *p-values* for *F-tests* to determine whether the more complex model including earnings forecast errors is significantly better in explaining portfolio returns compared to the original model without earnings forecast errors. The results almost perfectly match the results for the estimated regressions: For regressions with a statistically significant earnings forecast errors coefficient, the *F-test* signals that the more complex model including earnings forecast errors is significantly better in explaining portfolio returns. Overall, the *F-test* favours the more complex model for 11 of the 25 portfolios in the Fama & French (2015) five-factor model setting and for 12 portfolios in both the Carhart (1997) four-factor model and the Hou et al. (2015) *q*-factor model, based on a *p-value* of less than 0.05.

This section reveals that the addition of earnings forecast errors as a proxy for mispricing to the popular Fama & French (2015) five-factor model, the Carhart (1997) four-factor model, and the Hou et al. (2015) *q*-factor model lowers the estimated betas of both the market

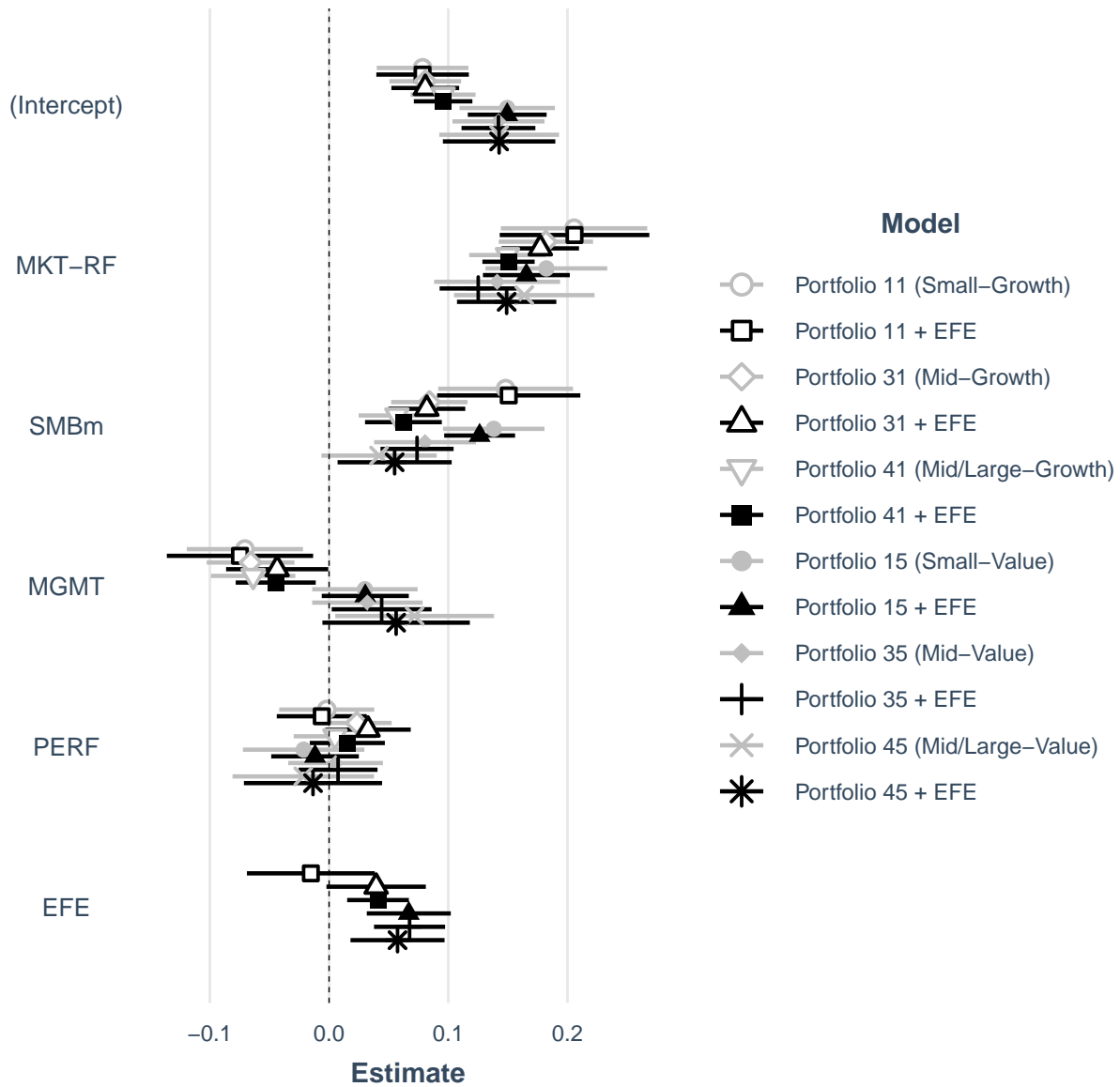
excess return and the value risk factor (HML). Conversely, adding earnings forecast errors has the effect of raising the estimated profitability risk premium (RMW). When significant, the coefficient for earnings forecast errors is strongly positive. This implies that less mispricing in the form of less negative earnings forecast errors corresponds to higher contemporaneous returns. The addition of earnings forecast errors raises the portion of variability explained in the returns of the 25 size- and book-to-market sorted portfolios, as measured by the adjusted R^2 , and is the preferred model for almost half of the tested portfolios. This effect is more pronounced for portfolios of large-cap and value stocks.

3.4.2 Robustness: Regressions with Stambaugh Mispricing Factors

In a next step we analyse how earnings forecast errors as a proxy for mispricing interact with other mispricing factors identified in prior literature. Specifically, we analyse the effect of adding earnings forecast errors to the four-factor model of Stambaugh & Yuan (2017), which includes two mispricing factors in addition to the market and size factor. We focus on the model of Stambaugh & Yuan (2017), as the authors find that this model is superior to both the Hou et al. (2015) q -factor model and the Fama & French (2015) five-factor model in explaining a large set of stock market anomalies.

Figure 9 illustrates the estimated regression coefficients for the Stambaugh & Yuan (2017) four-factor model. Similar to the other models, only a selected number of portfolios is presented for better readability. Additionally, the predictors are mean-centered and scaled by one standard deviation. Table 25 in the appendix presents the estimated regressions for the Stambaugh & Yuan (2017) four-factor model standing alone, and Table 26 presents them with earnings forecast errors as an additional explanatory variable.

Similar to the other three models, the estimated coefficient for the market excess return (MKT-RF) is reduced by 0.04, on average, when earnings forecast errors are added to the Stambaugh & Yuan (2017) four-factor model. Figure 9 shows that this drop is concentrated



The figure shows regression coefficients of the Stambaugh and Yuan four-factor model plus earnings forecast errors (EFE) in explaining annual excess returns on a selection of 25 size- and book-to-market sorted portfolios. Due to space limitations the results for only a limited number of portfolios are shown. The Stambaugh and Yuan four-factor model is comprised of the market excess return (RM-RF), the size factor of Stambaugh (SMBm), the mispricing factor related to variables that a firm's management can rather affect directly (MGMT) and the performance-related mispricing factor (PERF). Value-weighted portfolio earnings forecast errors in the sort for June of year t are defined as firms' actual trailing 12 month earnings per share measured in June $t+1$ minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t . Earnings forecast errors are trimmed every year at the 1% and 99% levels. All predictors are mean-centered and scaled by 1 standard deviation. The width of the confidence interval is 95% with heteroskedasticity-robust (HC1) standard errors as Newey and West (1987) standard errors are not available here.

Figure 9: Regressions of Stambaugh and Yuan four-factor model and earnings forecast errors

among value stocks: The estimated market betas for value stocks fall by 0.07, on average, while they remain stable for growth stocks. This provides further evidence that part of the perceived general stock market risk for value stocks might instead be uncertainty around earnings as measured by earnings forecast errors. Also mirroring the results of the other three tested models, adding earnings forecast errors has little effect on the magnitude of the size factor coefficients in the Stambaugh & Yuan (2017) model.

The first mispricing factor, “MGMT”, captures mispricing related to six anomaly variables that a firm’s management can affect rather directly. The significant coefficients for MGMT are found mostly among growth and value portfolios, with the difference that growth portfolios have a negative MGMT coefficient while value portfolios have a positive exposure to the factor. Adding earnings forecast errors to the four-factor model of Stambaugh & Yuan (2017) reduces the negative MGMT coefficient for growth stocks by 0.06, on average, while they remain stable for value-oriented portfolios. The second mispricing factor, “PERF”, is composed of five anomaly variables that are mainly related to performance measures. With annual return data in our analysis, the coefficient of PERF is significant only for five portfolios. Adding earnings forecast errors to the model has little effect on the PERF coefficients: They hardly change and remain mostly insignificant.

Most importantly, when earnings forecast errors are added to the Stambaugh & Yuan (2017) four-factor model, the coefficients for earnings forecast errors are significant for 18 of the 25 portfolios. It is thus the most significant mispricing factor, by far, among the three (EFE, MGMT, and PERF) included. Similar to the results for the Fama & French (2015) five-factor model, the Carhart (1997) four-factor model, and the Hou et al. (2015) q -factor model, the coefficient for earnings forecast errors is always strongly positive when significant. This implies that less mispricing in the form of less negative earnings forecast errors corresponds to higher contemporaneous returns. Also mirroring the results for the other three models, value portfolios carry the highest and most significant earnings forecast errors coefficients

when added to the Stambaugh & Yuan (2017) four-factor model. This indicates that earnings forecast errors capture a distinctly different form of mispricing, namely, uncertainty regarding earnings.

Table 11: Regression statistics for Stambaugh four-factor model

	Low B/M	2	3	4	High B/M
<i>adjusted R² without earnings forecast errors</i>					
Small	0.85	0.82	0.84	0.85	0.78
2	0.84	0.85	0.85	0.76	0.66
3	0.86	0.91	0.78	0.66	0.64
4	0.84	0.84	0.78	0.68	0.56
Big	0.87	0.87	0.85	0.64	0.35
<i>adjusted R² with earnings forecast errors</i>					
Small	0.84	0.81	0.86	0.87	0.85
2	0.84	0.87	0.88	0.76	0.70
3	0.87	0.92	0.82	0.78	0.77
4	0.87	0.87	0.85	0.72	0.61
Big	0.87	0.87	0.86	0.73	0.37
<i>F-statistic</i>					
Small	0.41	0.07	9.40	15.93	18.85
2	2.26	13.48	8.26	1.86	15.92
3	5.88	31.69	21.69	45.51	78.19
4	15.25	11.69	24.33	20.47	29.61
Big	0.98	0.71	7.44	16.24	1.04
<i>p-value (F-statistic)</i>					
Small	0.52	0.79	0.00	0.00	0.00
2	0.14	0.00	0.01	0.18	0.00
3	0.02	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00
Big	0.33	0.41	0.01	0.00	0.32

This table shows in the first two panels the adjusted R² measure of time series regressions of annual portfolio excess returns for 25 portfolios formed on size and the book-to-market ratio on risk-factor models for the 34 portfolio formation years from 1982-2015. Panels three and four show the F-statistic and corresponding p-value of F-tests comparing models with and without earnings forecast errors. The Stambaugh four-factor model is comprised of the market excess return (RM-RF), the size factor (SMBm) and two mispricing factors (MGMT and PERF). Value-weighted portfolio earnings forecast errors in year t are defined as firms' actual trailing 12 month earnings per share measured in June t+1 minus consensus 12 month expected earnings per share measured in June t scaled by total assets per share in year t. Test-statistics are calculated using Newey and West (1987) standard errors with four lags.

Lastly, Table 11 presents the adjusted R^2 measure for the estimated regressions for the Stambaugh & Yuan (2017) four-factor model without earnings forecast errors (first panel)

and with earnings forecast errors included (second panel). The addition of earnings forecast errors leads to a rise in the adjusted R^2 for all portfolios, except one, by 0.04, on average. The strongest effect is among value portfolios, where the adjusted R^2 rises substantially by 0.06, on average. The lower two panels report the F -statistics and corresponding p -values for F -tests that assess whether the more complex model including earnings forecast errors is significantly better in explaining portfolio returns compared to the original models without earnings forecast errors. It confirms that the more complex model including earnings forecast errors has a higher explanatory power for the returns for 18 portfolios that are exactly the 18 portfolios having a significant coefficient for the earnings forecast error variable.

3.5 Chapter Conclusion

Existing research, such as that by Stambaugh & Yuan (2017), indicates that factor models can be useful to examine whether expected returns reflect some sort of risk or mispricing. Factors may capture systematic risk where investors demand a risk premium as compensation for bearing that risk, or factors can capture sources of mispricing, such as investor sentiment or uncertainty regarding earnings. In this paper we examine how uncertainty about these earnings as proxied by earnings forecast errors contribute to the mispricing phenomenon. We focus on the Fama & French (2015) five-factor model, the Carhart (1997) four-factor model, and the Hou et al. (2015) q -factor model, as they largely summarise the cross-section of average stock returns. Furthermore, we add earnings forecast errors to the four-factor model of Stambaugh & Yuan (2017), which includes two mispricing factors, as the authors find that some form of mispricing is at least partially responsible for the many reported return anomalies.

We reveal that, when significant, the coefficient for earnings forecast errors is always strongly positive, which is mostly the case for large-cap portfolios. This implies that less mispricing in the form of less negative earnings forecast errors corresponds to higher contemporaneous

returns. Additionally, the coefficient for earnings forecast errors is, on average, five times higher for value stocks compared to growth stocks. Adding earnings forecast errors to existing risk-factor models lowers the estimated betas of the market excess return and the value risk factor for value stocks in all tested models. Thus, some of the perceived general stock market risk and the value premium might instead be uncertainty regarding earnings as measured by earnings forecast errors. Moreover, when added to the Stambaugh & Yuan (2017) four-factor model, earnings forecast errors are the most significant mispricing factor, by far, among the three included. This demonstrates that they capture a distinctively different mispricing aspect not captured by the other two mispricing factors, namely, uncertainty regarding earnings. Overall, adding earnings forecast errors to existing risk-factor models significantly raises the portion of variability explained in the returns of the 25 size- and book-to-market sorted portfolios as measured by the adjusted R^2 measure for all four tested models. This effect is more pronounced for large-cap and value stocks, where the more complex model including earnings forecast errors is significantly better in explaining portfolio returns. These empirical results highlight the importance of understanding the driving forces behind earnings forecast errors and their broad empirical power in the cross-section of stock returns.

One limitation of our study is that earnings forecast errors, and thus all other variables as well, are measured at an annual frequency, which limits the number of observations in our sample substantially. The studies closest to ours such as Fama & French (2015), Hou et al. (2015), and Stambaugh & Yuan (2017) estimate regression models at a monthly frequency. This needs to be taken into account when comparing these studies with our study. Follow-up studies might examine earnings forecast errors over various forecast horizons (other than 12 months) and at a higher frequency. The limitation is that mispricing, in the form of earnings forecast errors, needs some time to materialize in order to be measurable. Furthermore, future research might expand on the set of mispricing factors to examine their interaction with earnings forecast errors as well.

4 Risk of Momentum: An International Comparison²¹

4.1 Chapter Introduction

Momentum strategies usually buy past winners and sell past losers, which implies a bet on past returns predicting future returns in the cross-section. The academic literature reveals that the success of momentum strategies is not limited to U.S. stocks, where it was first identified by Jegadeesh & Titman (1993), but is a widespread phenomenon across major asset classes, regions, and periods. However, investors pay a high price for the strong momentum returns, as they are highly negatively skewed and suffer from infrequent but severe drawdowns. For example, the winners-minus-losers (WML) strategy from Fama and French lost 91.59% within two months in 1932 and returned -73.43% within three months in 2009 (Barroso & Santa-Clara, 2015, p. 112).

Studies such as those by Barroso & Santa-Clara (2015) and Daniel & Moskowitz (2016) also show that the risk of momentum varies substantially over time and is highly predictable in the United States. Based on *ex ante* volatility forecasts for momentum, a dynamically weighting of the momentum factor WML leads to a doubling of the Sharpe ratio compared to the regular momentum strategy in both studies. Additionally, Barroso & Santa-Clara (2015) find that a dynamic weighting of the momentum factor based on an autoregressive (AR) variance forecast largely eliminates the crash risk of momentum.

In this paper we build on the findings of Barroso & Santa-Clara (2015) and examine whether the predictability of the risk of momentum can be generalised to all developed market equity regions, i.e. the United States, Europe, Japan, and the Asia Pacific ex Japan region. Further, we apply the AR forecast of Barroso & Santa-Clara (2015) for the variance of momentum to all five Fama and French factors and test whether the predictability of risk is a pervasive phenomenon across all five risk factors. Lastly, we investigate the potential impact of the

²¹unpublished working paper

publication of the Barroso & Santa-Clara (2015) study on the predictability of risk and the success of the risk-managed momentum strategy.

Using daily and monthly returns for the six risk factors from Kenneth R. French's website, we find that the risk of momentum is not only predictable in the United States but generally in all other developed market equity regions, in other words, Europe, Japan, and the Asia Pacific ex Japan region. We further demonstrate that the high autocorrelation of momentum risk is limited not only to the first lag but is statistically significant for up to approximately 10 lags based on monthly data. Importantly, we reveal that the predictability of the variance is not unique to the momentum strategy but is a common characteristic that applies to all five Fama and French factors, i.e. the market excess return (RMRF), size (SMB), value (HML), profitability (RMW) and investment (CMA) factor. We find that the risk of the investment factor, which is not included in the analysis of Barroso & Santa-Clara (2015), and that of the value factor demonstrate an ever higher persistence than momentum, on average, across the four regions. Furthermore, the persistence in risk varies substantially by region: The AR(1) coefficients across all six factors average approximately 0.66 in both the U.S. and Europe, 0.55 in Japan, and only 0.48 in the Asia Pacific ex Japan region.

We further demonstrate that a risk-managed investment strategy based on an AR(1) volatility forecast and a volatility target approach substantially improves the risk-return profile of the momentum strategy, mainly by improving the skewness and kurtosis and thus reducing its crash risk. Our result is consistent with that of Barroso & Santa-Clara (2015), who arrive at similar results for the lengthy sample period 1927-2011. We find that the risk-managed momentum strategy remains highly successful relative to the plain momentum strategy, even after it was proposed by Barroso & Santa-Clara (2015). However, we find that the same strategy fails to improve the risk and return measures for the other factors despite the high predictability of their risk. Lastly, when we decompose the risk of momentum, we find that the vast majority of the risk is strategy-specific and not driven by the variance of the broad

stock market. This confirms the results of Barroso & Santa-Clara (2015) and might explain the strong success of the risk-managed strategy of momentum.

Importantly, the time series of the variance of momentum and its residuals from AR(1) first-order AR models are highly autocorrelated. Thus, as opposed to Barroso & Santa-Clara (2015), our empirical results are based on heteroskedasticity- and autocorrelation-consistent (HAC) standard errors to circumvent this issue.

The layout of the paper is as follows: Section 4.2 summarises the related literature, and Section 4.3 describes the sample data, the measurement of momentum, and the methodology. Section 4.4 presents the empirical results, and Section 4.5 concludes.

4.2 Literature Review

Momentum was first identified by Jegadeesh & Titman (1993), who found that, among U.S. stocks, previous winners outperform previous losers by as much as much 1.49% per month. These strong returns were a puzzle, as the abnormal strong returns of momentum could not be explained by the three Fama & French (1993) risk factors of market excess return (RMRF), size (SMB), and value (HML), in addition to their negative correlation to the market and value factor. In the following years, it became apparent that momentum is not just a U.S. stock market anomaly: Rouwenhorst (1998) and Rouwenhorst (1999) found evidence of momentum in international equity markets; Asness, Liew, & Stevens (1997) discovered momentum in stock market country indices; Moskowitz & Grinblatt (1999) documented momentum in industry stock portfolios; Okunev & White (2003) and Menkhoff, Sarno, Schmeling, & Schrimpf (2012) found evidence of momentum in currency markets; Erb & Harvey (2006) discovered momentum in commodity markets; and Asness et al. (2013) documented momentum across major asset classes.

However, investors paid a high price, as the strong returns of momentum strategies were highly negatively skewed and suffered from infrequent but severe drawdowns: The winners-

minus-losers (WML) strategy from Fama and French lost 91.59% within two months in 1932 and returned -73.43% within three months in 2009 (Barroso & Santa-Clara (2015), p. 112). Thus, many studies have focussed on the risk properties of momentum strategies: Grundy & Martin (2001) found that the two largest momentum crashes occurred after a broad stock market drawdown. They demonstrated that the equity momentum strategy has time-varying stock market betas. After a market drawdown, the winner stocks in the momentum portfolio tend to be low-beta stocks, while the past loser stocks tend to be high-beta stocks. Therefore, the overall winners-minus-losers strategy has a negative stock market beta during a stock market recovery. Grundy & Martin (2001) argued that managing these time-varying market betas will help avoid future large momentum crashes.

Daniel & Moskowitz (2016) revealed that momentum crashes are forecastable, to some extent: They found that, in bear markets and especially when market volatility is high, past loser stocks carry a low downside market beta but a very high upside market beta. This optionality is not fully reflected in their prices, resulting in the expected returns of past loser stocks becoming very high. Subsequently, the strong momentum returns are partly reversed during these times. Under the objective of maximising the in-sample Sharpe ratio, Daniel & Moskowitz (2016) used equity bear market indicators and *ex ante* volatility forecasts to estimate the mean return and volatility of the momentum time series for the next month. Based on these estimates, a dynamically weighting of the momentum factor WML leads to a doubling of the Sharpe ratio compared to the plain momentum strategy. A range of explanations, such as compensation for crash risk or volatility risk, or the three Fama & French (1993) factors, cannot fully explain their results.

In a similar direction, Wang & Xu (2015) found that the volatility of the broad stock market has significant predictive power for the momentum strategy, where the predictive power of the market volatility is concentrated among the past loser stocks. The default risk, especially during volatile bear markets, helps to explain part but not all of the predictive power of the

market volatility.

While Grundy & Martin (2001), Wang & Xu (2015), and Daniel & Moskowitz (2016) analysed the time-varying systematic risk of momentum, Barroso & Santa-Clara (2015) focussed on momentum-specific risk and proposed a different method to manage the downside risk. They found that the risk of momentum, based on realized variances of daily returns, is highly predictable. An autoregressive (AR) model on monthly variances yields an out-of-sample R-square of 57.82% (in-sample: 49.10%). This R-square is almost 20% higher than a similar AR(1) model for the variance of the market risk factor, which, in turn, has already been documented to be highly predictable; see, for example, Engle & Bollerslev (1986) and Schwert (1989). In a next step, Barroso & Santa-Clara (2015) computed a monthly AR forecast for the variance of momentum to scale the weight to the momentum factor WML based on the variance forecast and a constant volatility target. This risk-managed investment strategy substantially increased the Sharpe ratio of momentum. Probably even more important to most investors, the risk-managed strategy reduced the higher-order risks substantially: The high excess kurtosis was markedly reduced and the very negative skewness improved substantially and, in some samples, even turned positive.

4.3 Data and Methodology

Our sample data is composed of risk factor returns for the four regions United States, Europe, Japan, and Asia Pacific ex Japan.²² The returns for all regions are calculated in U.S. dollars and include dividends and capital gains. The daily and monthly returns for the five risk factors market excess return (RMRF), size (SMB), value (HML), profitability (RMW), investment (CMW), plus the momentum (WML) factor are from Kenneth R. French's website for all regions.²³ Based on the data availability for developed market factors outside the United

²²Europe is composed of Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, Great Britain, Greece, Ireland, Italy, Netherlands, Norway, Portugal, and Sweden. The Asia Pacific region excluding Japan is composed of Australia, Hong Kong, New Zealand, and Singapore.

²³http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/

States, the sample is limited to the period from December 1990 until April 2020 (353 months). For the United States, the market factor (RMRF) is the excess return on the market, calculated as the value-weighted return of all of the CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 (NYSE common excluding foreign, ADRs, REIT, closed-end funds) or 11 (NYSE/NYSE American common excluding foreign, ADRs, REIT, closed-end funds) at the beginning of month t , valid shares and price data at the beginning of t , and valid return data for t minus the one-month U.S. Treasury bill rate, which is from Ibbotson Associates. For Europe, Japan, and Asia Pacific ex Japan, the market factor (RMRF) is the return on a region's value-weighted market portfolio minus the one-month U.S. Treasury bill rate.

For the construction of the size (SMB), value (HML), profitability (RMW), and investment (CMW) factors, Fama & French (2015) use the six value-weighted portfolios formed on size and the book-to-market ratio, the six value-weighted portfolios formed on size and operating profitability, and the six value-weighted portfolios formed on size and investment (18 portfolios in total). These portfolios are constructed by sorting stocks in a region into two size and three respective book-to-market (B/M), operating profitability (OP), and investment (INV) groups.²⁴ In a next step, Fama & French (2015) define the size factor SMB (Small Minus Big) as the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios:

²⁴For more details on the measurement of the variables, the breakpoints, and the stock universe, see https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/six_portfolios.html, https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/six_portfolios_me_op.html, https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/six_portfolios_me_inv.html.

$$SMB_{B/M} = \frac{1}{3}(Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3}(Big\ Value + Big\ Neutral + Big\ Growth)$$

$$SMB_{OP} = \frac{1}{3}(Small\ Robust + Small\ Neutral + Small\ Weak) - \frac{1}{3}(Big\ Robust + Big\ Neutral + Big\ Weak)$$

$$SMB_{INV} = \frac{1}{3}(Small\ Conservative + Small\ Neutral + Small\ Aggressive) - \frac{1}{3}(Big\ Conservative + Big\ Neutral + Big\ Aggressive)$$

$$SMB = \frac{1}{3}(SMB_{B/M} + SMB_{OP} + SMB_{INV})$$

The value factor HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios:

$$HML = \frac{1}{2}(Small\ Value + Big\ Value) - \frac{1}{2}(Small\ Growth + Big\ Growth)$$

The profitability factor RMW (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios:

$$RMW = \frac{1}{2}(Small\ Robust + Big\ Robust) - \frac{1}{2}(Small\ Weak + Big\ Weak)$$

The investment factor CMA (Conservative Minus Aggressive) is the average return on the two

conservative investment portfolios minus the average return on the two aggressive investment portfolios:

$$CMA = \frac{1}{2}(Small\ Conservative + Big\ Conservative) - \frac{1}{2}(Small\ Aggressive + Big\ Aggressive)$$

A description of the construction of the momentum factor (Mom; WML), which is also briefly described in Fama & French (2012) p. 460, is taken from Kenneth French's website:²⁵

We use six value-weight portfolios formed on size and prior (2-12 [month]) returns to construct Mom. The portfolios, which are formed monthly, are the intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on prior (2-12) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles. Mom is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios:

$$Mom = \frac{1}{2}(Small\ High + Big\ High) - \frac{1}{2}(Small\ Low + Big\ Low)$$

Table 12 presents the summary statistics based on monthly returns for the six risk factors for all regions. Besides the market risk factor (RMRF), the momentum factor (WML) has the highest annualised mean average excess return in the U.S., Europe, and the Asia Pacific ex Japan region, but also the highest standard deviation. Additionally, the distribution of monthly momentum returns is leptokurtic (i.e., it has more outliers compared to a normal distribution) and is highly negatively skewed, meaning, it has more extreme negative returns. This is further underpinned by the fact that momentum has the worst monthly returns among

²⁵https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html

all factors in all regions (see also Daniel & Moskowitz (2016)). In Japan, we confirm the well-documented empirical failure of the momentum strategy for stock selection in Japan (see, e.g., Asness (2011)).

Table 12: Descriptive statistics for risk factors

	Mean Ret.	t-stat (Mean Ret.)	min. Ret.	max. Ret.	Std. Dev.	Kurtosis	Skewness	Sharpe
US								
RMRF	8.96	3.13	-17.23	13.65	14.92	1.48	-0.68	0.60
SMB	1.83	0.93	-14.91	18.32	10.57	4.72	0.42	0.17
HML	1.08	0.54	-14.12	12.87	10.76	2.96	-0.03	0.10
RMW	4.05	2.41	-18.34	13.33	8.97	11.05	-0.41	0.45
CMA	2.00	1.51	-6.86	9.56	7.13	2.39	0.61	0.28
WML	5.64	1.81	-34.39	18.36	16.53	10.78	-1.44	0.34
Europe								
RMRF	5.76	1.81	-22.03	13.67	16.79	1.74	-0.62	0.34
SMB	0.61	0.44	-7.41	8.81	7.45	0.99	-0.05	0.08
HML	2.81	1.76	-10.96	11.15	8.53	3.46	0.05	0.33
RMW	4.84	4.74	-4.84	6.08	5.43	0.80	-0.27	0.89
CMA	1.55	1.34	-7.33	8.75	6.24	3.72	0.40	0.25
WML	11.65	4.48	-26.10	13.65	13.43	7.84	-1.23	0.87
Japan								
RMRF	0.85	0.24	-16.22	16.87	18.77	0.62	0.20	0.05
SMB	1.23	0.60	-11.53	13.10	11.00	1.96	0.10	0.11
HML	3.15	1.69	-14.25	10.05	10.01	2.15	-0.20	0.31
RMW	1.59	1.16	-8.09	8.79	7.36	2.01	0.00	0.22
CMA	0.43	0.28	-12.99	7.54	8.19	4.33	-0.77	0.05
WML	1.01	0.37	-19.83	14.95	15.00	2.97	-0.46	0.07
Asia Pacific ex Japan								
RMRF	8.26	2.14	-26.00	20.52	20.23	2.60	-0.42	0.41
SMB	-1.93	-1.07	-11.43	13.30	9.91	2.83	0.44	-0.20
HML	6.96	3.56	-8.91	23.70	10.30	10.67	1.45	0.68
RMW	3.57	2.06	-12.20	11.14	9.25	3.06	-0.17	0.39
CMA	3.74	2.42	-7.65	8.45	8.27	1.88	0.06	0.45
WML	10.35	3.62	-36.77	10.88	14.84	19.87	-2.93	0.70

This table compares the performance statistics of the momentum factor (WML, winners minus losers) with the Fama and French risk factors market (RMRF), size (SMB), value (HML), profitability (RMW) and investment (CMA). All statistics are computed with monthly returns. Reported are the mean average excess return (annualized) and t-statistics, the minimum and maximum one-month return in the sample period, the (annualized) standard deviation, excess kurtosis, skewness and the annualized Sharpe ratio. The sample period is from 1990:11 to 2020:04 (354 months).

Some studies suggest that one reason for the high excess kurtosis in investment strategies could be time-varying risk (see, e.g., Engle (1982), Bollerslev (1987)). Based on this we analyse the properties and the predictability of the risk in momentum strategies and compare this to the five Fama and French factors. Specifically, we follow Barroso & Santa-Clara (2015) and calculate the monthly realised variance RV of factor i in month t as the sum of squared

daily returns in the previous 21 trading days in each month

$$RV_{i,t} = \sum_{j=1}^{21} r_{i,d_t-j}^2$$

where r are the daily returns of factor i and $d_t - j$ is the time series of the dates of the last 21 trading days in each month. Table 13 illustrates summary statistics of the variances of the Fama and French risk factors for the United States, Europe, Japan, and Asia Pacific ex Japan. We find that, besides the market factor, the variance of the momentum factor (WML) is the highest and also the most volatile among all factors in all regions. This contrasts somewhat with the results of Barroso & Santa-Clara (2015), who found that the risk of momentum was the most volatile among their set of tested factors (RMRF, SMB, HML, and WML), albeit over a longer sample period, 1927-2011. The Breusch-Godfrey (BG) test for serial correlated errors indicates that autocorrelation in the errors is present in AR(1) models for the variances of the value (HML), profitability (RMW), investment (CMA), and momentum (WML) factors in all four regions.

Figure 10 presents the realised monthly variance of the momentum strategy in the four regions as well as their autocorrelations. The variances vary substantially over time, ranging, for example, in the United States from a minimum of 0.27 to a maximum of 236.3. Additionally, the variance of the momentum strategy is highly autocorrelated for up to 10 lags in the United States and Europe and to a slightly lesser extent also in Japan. In the Asia Pacific ex Japan region, the autocorrelation coefficient falls substantially after the first lag but remains weakly significant for up to 10 lags as well.

To test the predictability of the risk in momentum strategies and other risk factors, we estimate the following first-order autoregressive model where we regress the non-overlapping variance on its own lagged value plus a constant:

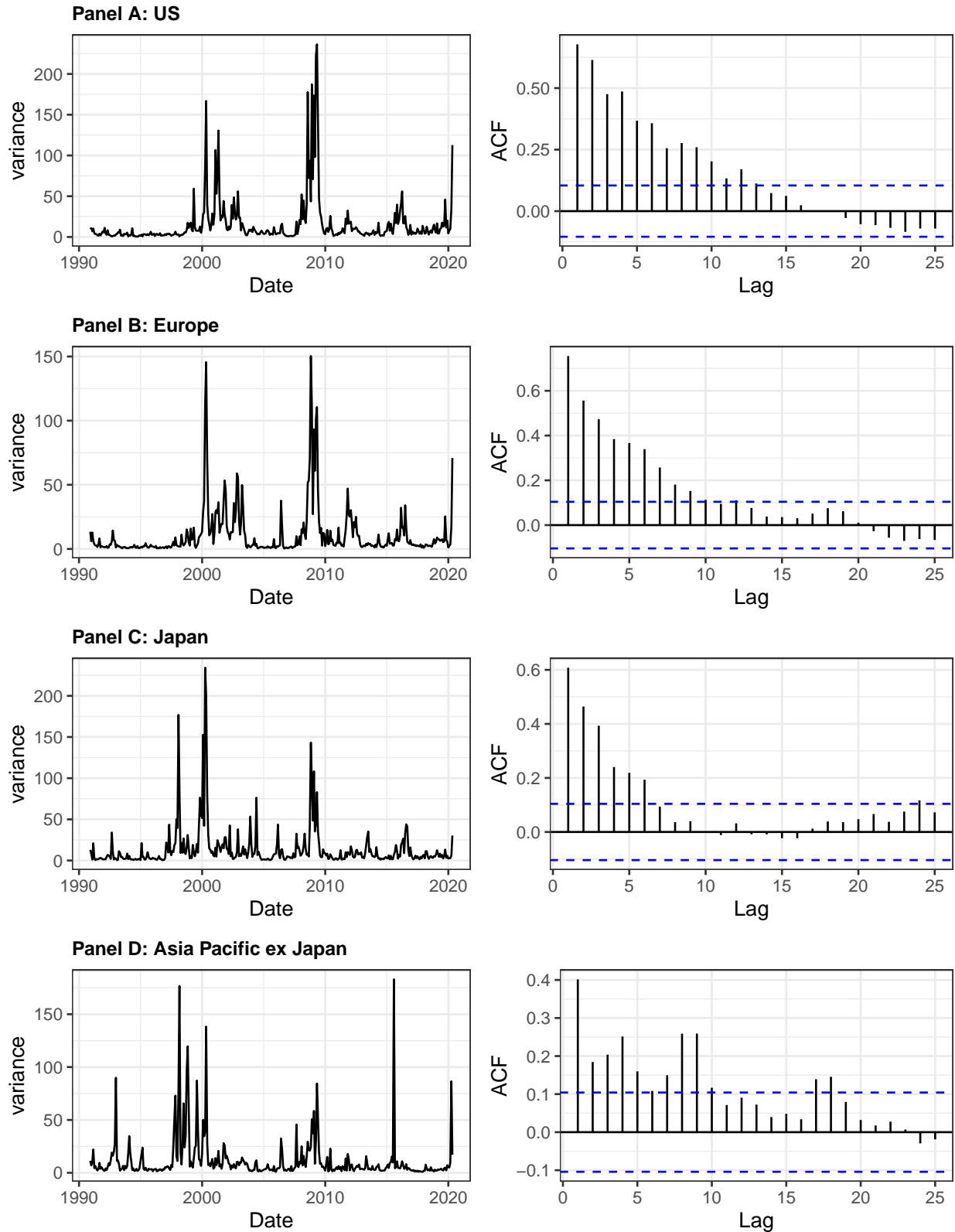
$$RV_{i,t} = \alpha + \beta RV_{i,t-1} + \varepsilon_t$$

Table 13: Descriptive statistics for variances of risk factors

	Mean	Std. Dev.	BG statistic	BG p-value
US				
RMRF	27.23	56.14	6.18	0.80
SMB	7.07	8.94	8.32	0.60
HML	7.98	14.58	65.84	0.00
RMW	4.31	7.79	48.70	0.00
CMA	3.53	5.74	126.65	0.00
WML	15.74	30.17	56.50	0.00
Europe				
RMRF	26.98	45.79	9.72	0.47
SMB	7.27	10.91	17.41	0.07
HML	3.97	6.19	30.76	0.00
RMW	1.70	2.34	18.16	0.05
CMA	2.20	3.31	34.80	0.00
WML	10.99	19.75	24.81	0.01
Japan				
RMRF	38.83	46.31	10.04	0.44
SMB	9.06	9.72	6.63	0.76
HML	5.98	8.02	50.64	0.00
RMW	3.91	5.45	62.41	0.00
CMA	3.95	6.26	57.05	0.00
WML	13.52	25.47	22.19	0.01
Asia Pacific ex Japan				
RMRF	23.54	45.24	12.71	0.24
SMB	6.89	10.44	13.43	0.20
HML	6.12	6.81	28.38	0.00
RMW	5.43	6.44	42.88	0.00
CMA	5.05	6.80	33.06	0.00
WML	11.84	21.37	32.07	0.00

This table compares descriptive statistics of the monthly variances of momentum (WML, winners minus losers) with the monthly variances of the Fama and French risk factors market (RMRF), size (SMB), value (HML), profitability (RMW) and investment (CMA). Realized variances are defined as the sum of squared daily returns in the previous 21 trading days. Reported are the mean and standard deviation of the monthly variances as well as the test statistic and p-value for the Breusch-Godfrey (BG) error autocorrelation test in AR(1) models on the monthly factor variances with up to 10 lags in the errors. The sample period is from 1990:11 to 2020:04 (354 months).

As Table 13 and Figure 10 illustrate, the time series of the variance of momentum strategies and its residuals from the AR(1) model are highly autocorrelated. While autocorrelation in the errors does not produce biased coefficient estimates, it produces incorrect standard errors



This figure shows the monthly time series of realized variances for the momentum strategy (left) as well as their autocorrelations for up to 25 lags (right) with the broken lines indicating the 95 percent confidence interval in the four regions US, Europe, Japan and Asia Pacific ex Japan. Realized variances are defined as the sum of squared daily returns in the previous 21 trading days. The sample period is from 1990:12 to 2020:04 (353 months). Daily returns for the momentum strategies are from Kenneth French' website.

Figure 10: Variance of momentum and its autocorrelation

and thus causes misleading inference. Heteroskedasticity- and autocorrelation-consistent (HAC) estimators of the variance-covariance matrix circumvent this issue and thus we use HAC-consistent standard errors in our empirical results.

4.4 Empirical Results

4.4.1 First-Order Autoregressive Models

Table 14 presents the results of AR(1) models of the realised variances of WML (momentum), RMRF (market), SMB (size), HML (value), RMW (profitability) and CMW (investments). The table illustrates the coefficients as well as the t -statistics of the first lag based on HAC-consistent standard errors. What is striking is that the coefficients are highly significant (p -value < 1%) for all six factors in all four regions. Thus, the predictability of the variance is not unique to the momentum strategy but rather a common characteristic to all risk factors. Barroso & Santa-Clara (2015) found that the risk of momentum is the most persistent, with a monthly AR(1) coefficient of 0.77 for the United States in the sample period July 1963 until December 2011. This is 0.19 higher than for the market factor and also higher than for the size factor (0.33) and the value factor (0.73). In our shorter, more recent sample from December 1990 until April 2020, we find that the risk of momentum is also very persistent: The AR(1) coefficient for momentum is, on average, 0.62 among the four regions and varies between 0.40 in Asia Pacific ex Japan, 0.61 in Japan, 0.70 in the U.S. and 0.78 in Europe. However, the risk of momentum in our sample is not the most persistent as opposed to Barroso & Santa-Clara (2015): We find that the risk of the investment factor (CMA), which is not included in the analysis of Barroso & Santa-Clara (2015), has an even higher AR(1) coefficient of 0.69, on average, across the four regions. For the value factor (HML) in the U.S., we estimate an AR(1) coefficient of 0.74, which almost perfectly matches the 0.73 estimate of Barroso & Santa-Clara (2015) even if the two sample periods differ substantially. In the other three regions, the AR(1) coefficient of the risk of the value factor also reveals a high

persistence of approximately 0.60.

The persistence of the risk of the market excess return (RMRF) in the U.S. seems to have declined over time: Barroso & Santa-Clara (2015) reported an AR(1) coefficient of 0.60 for the long sample period from 1927 until 2011 and 0.58 for the shorter period between 1963 and 2011. In our more recent sample from 1990 to 2020, we find an AR(1) coefficient of only 0.49. Additionally, the portion of variation explained of the market risk as measured by the adjusted R^2 declines from 36% for the long sample period from 1927 until 2011 in Barroso & Santa-Clara (2015) to 24% in our sample starting 1990.

Interestingly, the AR(1) coefficients and fraction of variation explained varies substantially by region: The AR(1) coefficients across all six strategies average approximately 0.66 in both the United States and Europe, 0.55 in Japan, and only 0.48 in the Asia Pacific ex Japan region. This is mirrored by the portion of variation explained by the first autocorrelation factor: The adjusted R^2 measure averages approximately 44% in the U.S. and Europe, 31% in Japan, and only 23% for the Asia Pacific ex Japan region. Looking across factors, the average AR(1) coefficient for most factors is in a relatively narrow range: The investment factor (CMA) has the highest AR(1) coefficient, on average, across the four regions (0.69), followed by the value factor HML (0.65) and the momentum factor (0.62). The market risk is the least predictable based on this measure, but the AR(1) coefficient still averages 0.46 across the four regions. This pattern is further confirmed by the adjusted R^2 measure, where the risk in the investment factor (CMA) has the highest fraction of variation explained (48%, on average) followed by the value factor (41%, on average, across all regions). For the momentum factor, we can confirm the findings of Barroso & Santa-Clara (2015) that approximately half of the risk in the momentum strategy is predictable in the U.S. (adjusted R^2 : 47%) and also in Europe (adjusted R^2 : 58%). However, in Japan, where the momentum strategy does not produce statistically significant returns, the risk of the strategy is largely not predictable by the AR(1) coefficient.

4.4.2 Decomposition of Momentum Risk

4.4.2.1 Market Variance and Momentum Variance In a next step, we analyse what is driving the high autocorrelation of the risk in momentum strategies. A well-documented finding in the momentum literature is that momentum strategies have time-varying market betas (see, e.g., Grundy & Martin (2001), Moskowitz, Ooi, & Pedersen (2012)). Thus, in a logical next step, Moskowitz et al. (2012) attempted to use market betas to hedge the risk in momentum strategies, which failed in real time. As Barroso & Santa-Clara (2015) indicated, this is because time-varying market betas are not the main source of the high predictability of momentum risk.

Thus, in a first step to decompose the risk of momentum strategies, we use the “market model” as labelled by Barroso & Santa-Clara (2015) and split the risk of momentum in market risk and (momentum) specific risk:²⁶

$$RV_{WML,t} = \alpha + \beta RV_{RMRF,t} + \varepsilon_t$$

Table 15 indicates that the market variance, indeed, has a positive effect on the momentum variance with a statistically significant coefficient in the U.S., Europe, and Japan of approximately 0.25. However, the market component βRV_{RMRF} accounts for only 21% of the variance in the total risk of momentum in the U.S. (38% in Europe, 21% in Japan, and 15% in the Asia Pacific ex Japan region). Thus, the vast majority of the risk of momentum is strategy-specific.

4.4.2.2 Predictability of Risk Components To further analyse the nature of the risk of momentum, we further decompose the risk and analyse the predictability of the various components. Table 16 presents the results of AR(1) regressions on each component of risk,

²⁶Barroso & Santa-Clara (2015) estimated this model without intercept and the square of the market beta and the square of the momentum specific term ε_t while we include the intercept term and use the market beta and momentum specific term without squaring it.

Table 15: Market Variance and Momentum Variance

	US	Europe	Japan	Asia Pacific ex Japan
(Intercept)	9.06*** (3.86)	3.79** (3.16)	3.62** (2.92)	7.53*** (3.66)
RV(RMRF)	0.24* (2.47)	0.27*** (5.70)	0.25*** (7.41)	0.18 (1.88)
R ²	0.21	0.38	0.21	0.15
Adj. R ²	0.21	0.38	0.21	0.15
Num. obs.	354	354	354	354

This table shows non-overlapping regressions of the realized variance of momentum (WML) on the realized variance of the market excess return (RMRF). Realized variances are defined as the sum of squared daily returns in the previous 21 trading days. The sample period is from 1990:12 to 2020:04 (353 months). Daily returns for the momentum factor and the market excess return are from Kenneth French' website. T-statistics are shown in parentheses, which are calculated using heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. Coefficients with $p < 0.05$ are shown in **bold**. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

which indicates that the various components do not have the same degree of predictability. We include the AR(1) regressions for the variance of momentum (WML; columns 1-4) and the variance of the market (RMRF; columns 5-8), which are already depicted in Table 14 again for a better comparison with the other components. Barroso & Santa-Clara (2015) finds that β^2 , estimated as a simple linear regression of momentum (WML) returns on market (RMRF) returns, is the least predictable component of momentum risk with an in-sample R^2 of only 5%.²⁷ We confirm the low predictability of β^2 in the U.S. with an R^2 of only 12% (column 13) and in the other regions as well. However, we find that β - in other words, the estimated non-squared beta on market excess returns - is highly predictable: The AR(1) coefficient is highly significant in all four regions, ranging from 0.67 (Asia Pacific ex Japan) to 0.81 (Europe), and the R^2 ranges from 45% to 65%. The last component is the momentum-specific risk, which is defined as the residual ε from regressions of the realised variance of momentum (WML) on the realised variance of the market excess return (RMRF); see Table 15. Barroso & Santa-Clara (2015) found that the square of the residual ε^2 is the most predictable component

²⁷Barroso & Santa-Clara (2015) estimated the squared beta from a simple linear regression of 126 daily returns of WML on the market factor (RMRF) based on six-month, non-overlapping periods. Because of our shorter sample, we estimate the monthly beta and squared beta from a linear regression of 21 daily returns of the WML factor on the RMRF (market) factor.

of momentum variance, with an in-sample R^2 of 52%. We also find that the residual ε is highly predictable with a significantly positive AR(1) coefficient in all four regions, ranging from 0.33 to 0.58. However, the R^2 is only 25% in the United States and 32% in both Europe and Japan in our more recent sample.

4.4.3 Risk-Managed Momentum Strategy

In a next step, we test whether the high predictability of momentum risk can be used to improve the higher-order risks of momentum, especially the high excess kurtosis and the negative skewness (see Table 12). Based on the same motivation, Barroso & Santa-Clara (2015) computed a monthly forecast for the variance of momentum to scale the weight to the momentum factor WML based on the variance forecast and a constant volatility target. We largely follow Barroso & Santa-Clara (2015) and calculate the monthly variance forecast for momentum based on the last 126 daily returns (six months) of the WML factor at each month-end as:

$$\hat{\sigma}_{WML,t}^2 = 21 \sum_{j=1}^{126} r_{WML,d_t-j}^2 / 126$$

where r_{WML,d_t-j}^2 are the daily squared returns of the momentum factor WML and $d_t - j$ is the time series of the dates of the last 126 daily returns at each month-end. With that, we seek to test two items: First, Barroso & Santa-Clara (2015) tested the risk-managed momentum strategy only for four selected developed markets (France, Germany, Japan, and the UK) besides the United States. We analyse whether the results of Barroso & Santa-Clara (2015) can be generalised to all developed market equity regions: the U.S., Europe, Japan, and the Asia Pacific region excluding Japan. Second, as a robustness check, we test whether the risk-managed momentum strategy of Barroso & Santa-Clara (2015) is still successful after the publication of their study in late 2014, as the strategy is easy to implement for asset managers and thus simple to exploit. To make our results comparable to the findings of Barroso & Santa-Clara (2015), we also set the annualised target volatility to 12%, which is

lower than the average standard deviation of WML of 15% across the four regions in our sample (see Table 12). The risk-managed momentum return $r_{WML^*,t}$ in month t is calculated as:

$$r_{WML^*,t} = \frac{\sigma_{target}}{\hat{\sigma}_t} r_{WML,t}$$

where σ_{target} is the annualised volatility target, $\hat{\sigma}_t$ is the monthly volatility forecast for WML, and $r_{WML,t}$ is the return for the regular momentum strategy in month t .

Table 17 presents the summary statistics for the risk-managed momentum strategies and Figure 11 the corresponding cumulative return plots, both for the full sample period (1990:06-2020:04) and after the publication of the Barroso & Santa-Clara (2015) study (2014:11-2020:04). Compared to the regular momentum strategy, the risk-managed strategy has a higher return in all four regions over the full sample period as well as after the publication of the Barroso & Santa-Clara (2015) study. This comes with a roughly similar standard deviation. Thus, the Sharpe ratio improves substantially, for example, in Europe from 0.90 for the regular momentum strategy to 1.64 for the risk-managed momentum strategy over the full sample period. In line with Barroso & Santa-Clara (2015), one of the most important improvements is at the higher-order risks: The risk-managed strategy removes the high negative skewness and high excess kurtosis of momentum in the U.S., Europe, and the Asia Pacific ex Japan region. Additionally, the worst monthly returns (column “min. Ret.”) are substantially improved in all regions except for Japan. Thus, the crash risk of momentum is significantly reduced.

Figure 12 illustrates the weights of the risk-managed momentum strategy to the WML factor in all four regions. The risk-managed strategies all have the lowest weight to WML in the early 2000s, related to the dot-com bubble, and in 2008 and 2009, related to the global financial crisis. Both were periods when the momentum strategy suffered large drawdowns during strong market recoveries. The dashed lines indicate the average weight to WML, which is above 1 in all four regions. This contrasts with Barroso & Santa-Clara (2015), who

reported an average weight to WML of 0.90 in the U.S., albeit over the much longer sample period of 1927:03-2011:12.

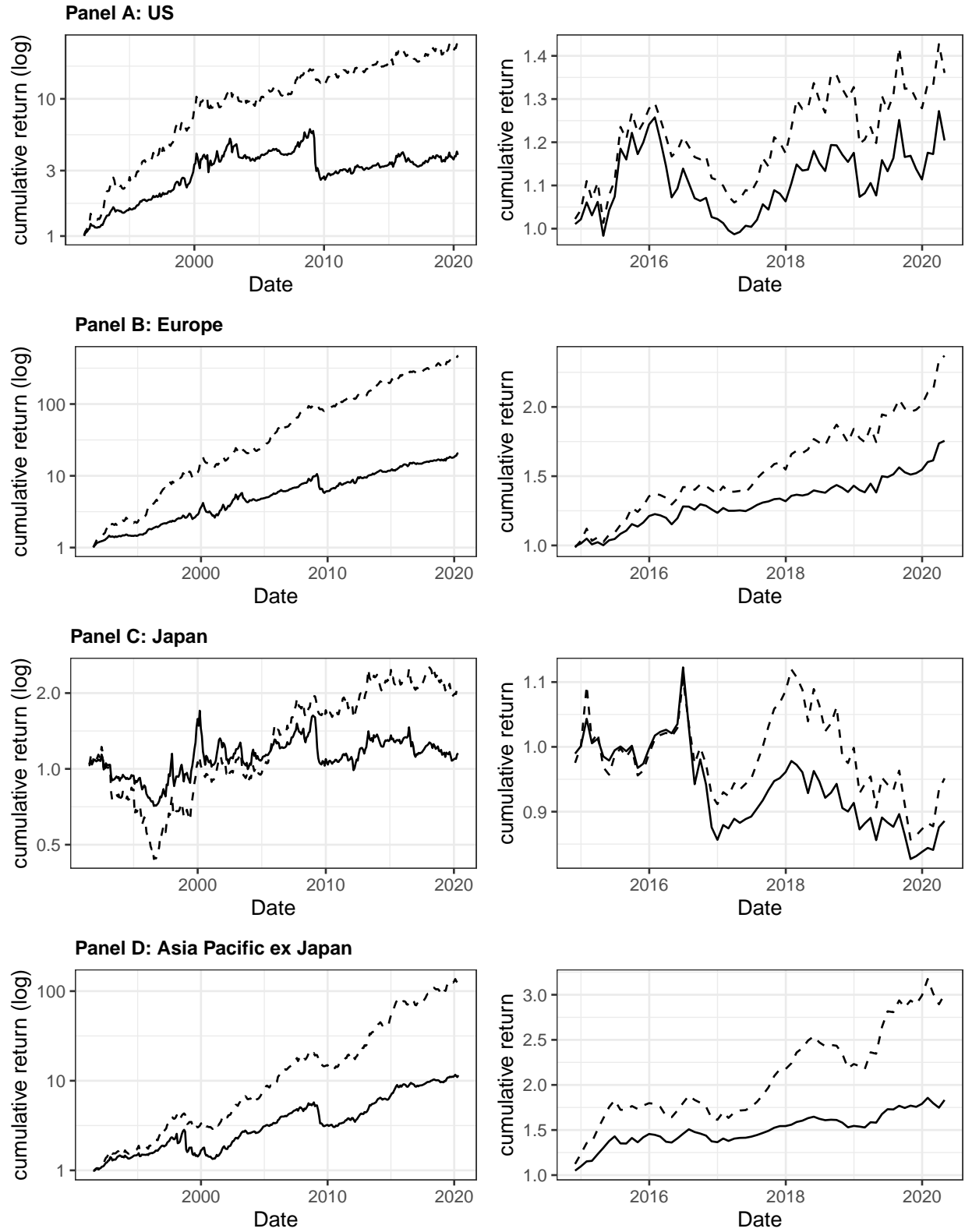
Table 17: Descriptive statistics for risk-managed momentum strategy

	Mean Ret.	t-stat (Mean Ret.)	min. Ret.	max. Ret.	Std. Dev.	Kurtosis	Skewness	Sharpe
US (1990:06 - 2020:04)								
WML	6.35	2.00	-34.39	18.36	16.56	10.99	-1.48	0.38
WML*	12.97	4.17	-20.54	18.04	15.79	2.24	0.09	0.82
US (2014:11 - 2020:04)								
WML	4.36	0.74	-8.68	10.33	13.48	0.02	0.14	0.32
WML*	6.79	1.09	-9.89	11.19	14.16	0.22	0.19	0.48
Europe (1990:06 - 2020:04)								
WML	12.08	4.58	-26.10	13.65	13.46	7.94	-1.24	0.90
WML*	25.12	7.96	-9.54	19.42	15.28	0.48	0.02	1.64
Europe (2014:11- 2020:04)								
WML	11.21	2.77	-4.40	8.49	9.04	0.61	0.55	1.24
WML*	17.94	2.98	-7.85	11.42	13.07	0.02	0.23	1.37
Japan (1990:06 - 2020:04)								
WML	1.61	0.58	-19.83	14.95	14.79	2.94	-0.37	0.11
WML*	3.99	1.33	-20.50	14.59	15.80	2.67	-0.61	0.25
Japan (2014:11 - 2020:04)								
WML	-1.68	-0.39	-8.50	8.44	10.18	1.52	-0.53	-0.16
WML*	-0.15	-0.03	-7.87	9.27	12.34	0.10	-0.23	-0.01
Asia Pacific ex Japan (1990:06 - 2020:04)								
WML	10.15	3.49	-36.77	10.88	14.94	19.69	-2.92	0.68
WML*	19.61	6.51	-19.30	13.94	14.89	1.58	-0.38	1.32
Asia Pacific ex Japan (2014:11 - 2020:04)								
WML	12.13	2.84	-5.44	6.45	9.49	-0.49	-0.02	1.28
WML*	23.57	3.20	-7.23	12.61	15.66	-0.18	0.29	1.51

This table compares the performance statistics of the risk-managed momentum strategy in the four regions US, Europe, Japan and Asia Pacific ex Japan over the full sample period (1990:06 - 2020:04) and after the study from Barroso and Santa-Clara (2015) has been published (2014:11 - 2020:04). The risk-managed momentum strategy uses the monthly realized variance forecast based on the previous 126 trading days (six months) and a target volatility of 12 per cent p.a. to scale the exposure to the momentum factor WML. Monthly realized variances are defined as the sum of squared daily returns in the previous 126 trading days, divided by 126 and then multiplied by 21 to get a monthly variance forecast. Daily and monthly returns for the momentum strategies are from Kenneth French' website.

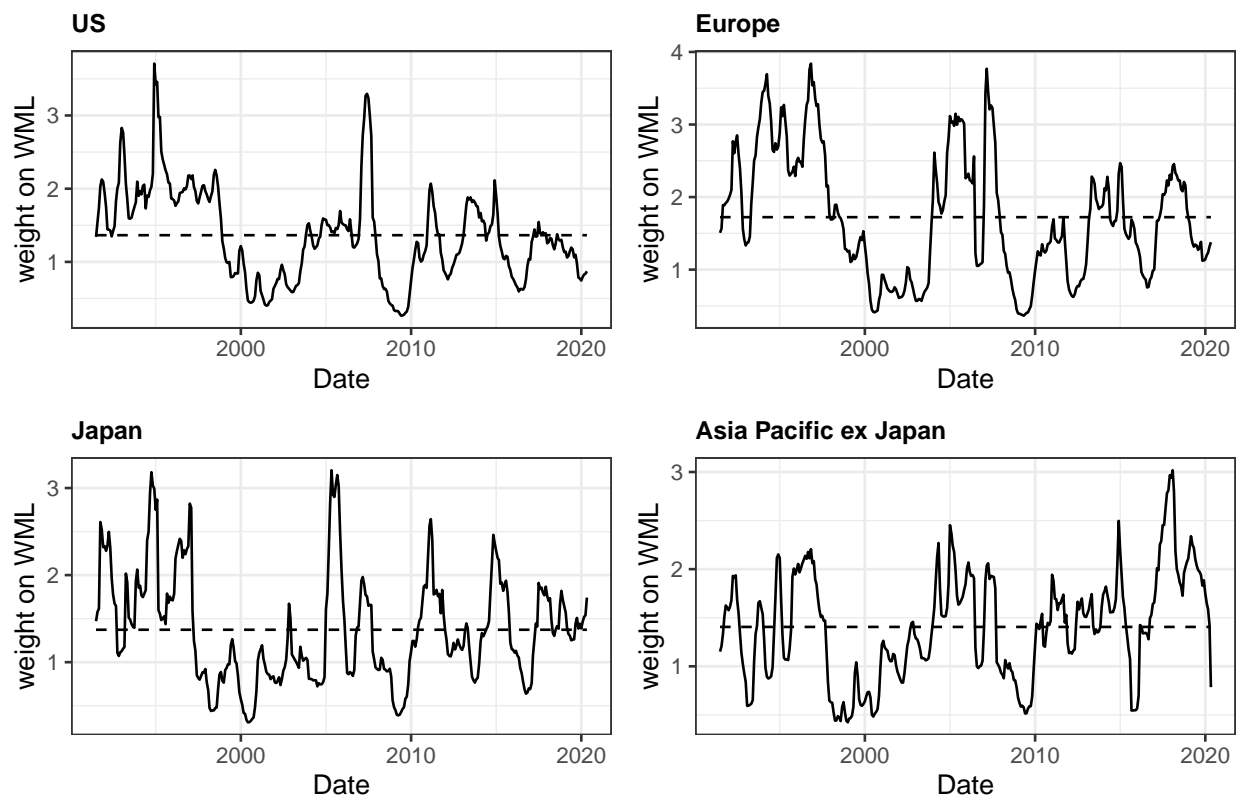
4.4.4 Risk-Managed Fama and French Factor Strategies

Based on the success of the risk-managed approach for the momentum strategy we also calculate a similar target volatility strategy for the five Fama and French factors. The calculation of the monthly variance forecast for each factor follows the calculation for momentum. Based on the last 126 daily returns (six months) of the respective factor at each



This figure plots the cumulative return of the standard (straight line) and risk-managed (dashed) momentum strategy WML (winners–minus–losers) in the four regions US, Europe, Japan and Asia Pacific ex Japan. The risk-managed momentum strategy uses the monthly realized variance based on the previous 126 trading days (six months) and a target volatility of 12 per cent p.a. to scale the exposure to the momentum factor WML. Monthly realized variances are defined as the sum of squared daily returns in the previous 126 trading days, divided by 126 and then multiplied by 21 to get a monthly variance forecast. The plots on the left-hand side show the cumulative return for the full sample period from 1990:06 to 2020:04 (347 months). The plots on the right-hand side show the cumulative return for the recent sample period from 2014:11 to 2020:04 (66 months) after the study from Barroso and Santa-Clara (2015) has been published. Daily and monthly returns for the momentum strategies are from Kenneth French' website.

Figure 11: Risk-managed momentum (WML) strategy



This figure plots the weights of the risk-managed momentum strategy to the momentum factor WML (straight line) and the average weight over the full sample (dashed line) in the four regions US, Europe, Japan and Asia Pacific ex Japan. The risk-managed momentum strategy uses the monthly realized variance based on the previous 126 trading days (six months) and a target volatility of 12 per cent p.a. to scale the exposure to the momentum factor WML. Monthly realized variances are defined as the sum of squared daily returns in the previous 126 trading days, divided by 126 and then multiplied by 21 to get a monthly variance forecast. The sample period is from 1990:06 to 2020:04 (347 months). Daily and monthly returns for the momentum strategies are from Kenneth French' website.

Figure 12: Weights of the risk-managed momentum strategy

month-end it is defined as:

$$\hat{\sigma}_{FF,t}^2 = 21 \sum_{j=1}^{126} r_{FF,d_t-j}^2 / 126$$

where r_{FF}^2 are the daily returns of the respective Fama and French factor and $d_t - j$ is the time series of the dates of the last 126 daily returns at each month-end. For the market factor (RMRF), we set the target volatility to 15% p. a., as the market factor has a higher volatility than momentum in most regions. For the size (SMB), value (HML), profitability (RMW), and investment (CMA) factors, we set the annualised target volatility to 9%, which is the average volatility of these factors across the four regions (see Table 12).

Table 18 presents the summary statistics for the risk-managed investment strategies (denoted with a "*") for the Fama and French factors, again since June 1990 and after the publication of Barroso & Santa-Clara (2015) in November 2014, while Figures 13-17 illustrate the corresponding plots of the cumulative wealth.

Overall, we find that a similar risk-managed strategy fails to consistently improve the risk and return measures for the Fama and French factors despite the high predictability of their risk. The strongest results are for the profitability factor (RMW) and here especially in Europe and the U.S., where the risk-managed approach substantially improves the mean return. However, this comes with a markedly higher standard deviation and, thus, the Sharpe ratio does not improve. The risk-managed strategy also substantially improves the return and Sharpe ratio of the market factor (RMRF) in all regions except Japan until the strong and sudden market correction in March 2020 related to the coronavirus pandemic, where the market risk was clearly underestimated. For the value factor (HML), the risk-managed approach improves the return over the full sample but fails to improve the weak returns of the value factor in recent years. For the size factor (SMB) and the investment factor (CMA), the risk-managed strategy does not add much value relative to the plain factor strategy.

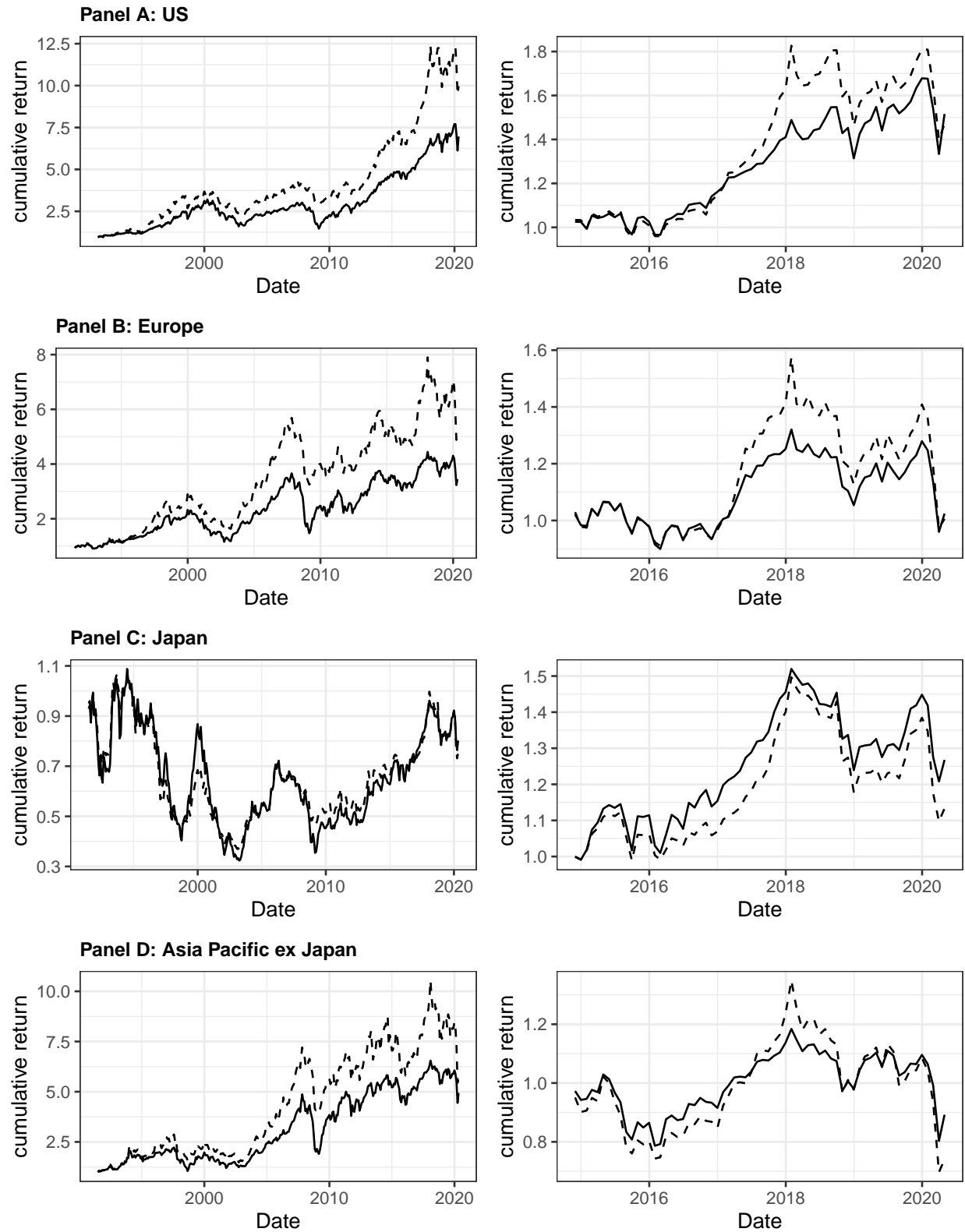
Table 18: Descriptive statistics for risk-managed factor strategies

	Mean Ret.	t-stat (Mean Ret.)	min. Ret.	max. Ret.	Std. Dev.	Kurtosis	Skewness	Sharpe
US (1990:06 - 2020:04)								
RMRF	8.15	2.83	-17.23	13.65	14.95	1.48	-0.66	0.55
RMRF*	9.41	3.37	-19.14	13.76	14.41	1.63	-0.73	0.65
SMB	1.42	0.72	-14.91	18.32	10.61	4.77	0.44	0.13
SMB*	1.11	0.55	-9.80	13.19	10.91	1.24	0.26	0.10
HML	1.36	0.67	-14.12	12.87	10.83	2.92	-0.05	0.13
HML*	2.11	0.96	-12.98	10.93	11.70	1.03	0.18	0.18
RMW	3.87	2.26	-18.34	13.33	9.04	10.91	-0.39	0.43
RMW*	5.23	2.44	-17.92	10.22	11.26	3.16	-0.49	0.46
CMA	2.53	1.90	-6.86	9.56	7.07	2.48	0.65	0.36
CMA*	2.83	1.46	-7.81	9.89	10.27	-0.05	0.22	0.28
US (2014:11 - 2020:04)								
RMRF	9.06	1.36	-13.39	13.65	14.96	2.17	-0.51	0.61
RMRF*	8.70	1.20	-14.81	12.22	16.31	1.88	-1.00	0.53
SMB	-3.60	-0.92	-8.45	6.81	9.30	0.53	-0.07	-0.39
SMB*	-4.51	-0.99	-9.80	9.22	10.94	1.15	0.05	-0.41
HML	-8.47	-1.89	-14.12	8.29	10.92	4.77	-0.61	-0.78
HML*	-8.63	-1.83	-12.98	9.83	11.53	2.99	-0.08	-0.75
RMW	2.06	1.01	-2.89	3.29	4.75	-0.26	-0.07	0.43
RMW*	3.38	0.94	-4.96	6.42	8.28	-0.12	0.04	0.41
CMA	-2.99	-1.28	-3.33	3.70	5.54	-0.04	0.55	-0.54
CMA*	-5.65	-1.36	-6.02	6.92	10.00	0.07	0.39	-0.57
Europe (1990:06 - 2020:04)								
RMRF	5.88	1.83	-22.03	13.67	16.85	1.75	-0.63	0.35
RMRF*	7.10	2.34	-18.14	11.43	15.82	0.87	-0.51	0.45
SMB	0.83	0.60	-7.41	8.81	7.43	1.05	-0.05	0.11
SMB*	0.46	0.29	-9.08	9.82	8.48	1.12	0.02	0.05
HML	2.84	1.75	-10.96	11.15	8.61	3.34	0.05	0.33
HML*	4.45	1.96	-15.40	9.14	11.96	1.72	-0.47	0.37
RMW	4.69	4.52	-4.84	6.08	5.47	0.76	-0.25	0.86
RMW*	12.73	5.49	-8.48	9.88	11.79	0.08	0.09	1.08
CMA	1.61	1.37	-7.33	8.75	6.27	3.73	0.40	0.26
CMA*	0.51	0.25	-9.87	10.32	11.02	0.72	-0.08	0.05
Europe (2014:11- 2020:04)								
RMRF	1.56	0.24	-15.44	6.70	14.85	1.44	-0.86	0.11
RMRF*	1.77	0.23	-18.14	11.43	17.99	1.77	-0.90	0.10
SMB	2.68	1.06	-5.09	4.74	5.84	0.93	-0.09	0.46
SMB*	2.00	0.54	-9.08	4.80	8.66	1.57	-0.67	0.23

HML	-6.86	-2.02	-10.96	6.36	8.24	5.12	-0.91	-0.83
HML*	-10.54	-2.19	-14.58	7.31	11.87	3.61	-0.99	-0.89
RMW	4.75	2.20	-3.85	3.25	4.97	0.22	-0.32	0.96
RMW*	12.66	2.59	-5.94	8.21	10.84	-0.23	0.06	1.17
CMA	-3.51	-1.94	-4.09	2.95	4.32	1.20	-0.01	-0.81
CMA*	-8.45	-2.07	-7.82	6.27	9.99	0.50	-0.06	-0.85
Japan (1990:06 - 2020:04)								
RMRF	0.96	0.28	-16.22	16.87	18.60	0.60	0.22	0.05
RMRF*	0.06	0.02	-12.76	14.50	14.38	0.95	-0.04	0.00
SMB	1.36	0.68	-11.53	13.10	10.68	1.98	0.05	0.13
SMB*	0.95	0.52	-9.39	9.99	9.81	0.92	-0.15	0.10
HML	3.23	1.70	-14.25	10.05	10.08	2.10	-0.20	0.32
HML*	3.84	1.78	-11.01	11.08	11.41	0.65	-0.12	0.34
RMW	1.46	1.07	-8.09	8.79	7.30	2.08	0.06	0.20
RMW*	1.67	0.85	-10.14	11.37	10.50	1.14	0.13	0.16
CMA	0.46	0.30	-12.99	7.54	8.25	4.27	-0.77	0.06
CMA*	1.72	0.79	-14.23	8.18	11.64	1.73	-0.66	0.15
Japan (2014:11 - 2020:04)								
RMRF	5.25	0.95	-10.09	9.26	12.72	0.92	-0.65	0.41
RMRF*	3.19	0.57	-12.76	7.26	13.03	2.55	-1.25	0.24
SMB	2.81	0.97	-4.99	3.95	6.73	0.38	-0.59	0.42
SMB*	3.07	0.81	-8.72	4.37	8.75	1.35	-0.91	0.35
HML	-4.33	-1.03	-6.99	6.44	10.03	-0.22	0.18	-0.43
HML*	-4.61	-1.05	-6.29	5.86	10.50	-0.66	0.07	-0.44
RMW	3.62	1.65	-2.89	3.59	5.05	-0.46	0.10	0.72
RMW*	6.54	1.53	-4.79	8.33	9.71	-0.15	0.26	0.67
CMA	-2.88	-1.21	-6.11	3.07	5.64	1.45	-0.71	-0.51
CMA*	-3.59	-0.78	-9.31	6.98	10.97	0.52	-0.56	-0.33
Asia Pacific ex Japan (1990:06 - 2020:04)								
RMRF	7.91	2.02	-26.00	20.52	20.34	2.58	-0.42	0.39
RMRF*	8.51	2.17	-25.49	23.78	20.33	2.43	-0.50	0.42
SMB	-1.63	-0.88	-11.43	13.30	9.97	2.80	0.42	-0.16
SMB*	-2.11	-1.01	-12.31	14.47	11.30	1.96	0.21	-0.19
HML	7.06	3.55	-8.91	23.70	10.38	10.49	1.43	0.68
HML*	8.60	4.08	-8.26	19.52	10.91	4.04	0.76	0.79
RMW	3.52	2.00	-12.20	11.14	9.31	3.03	-0.16	0.38
RMW*	3.66	1.84	-11.25	9.52	10.55	1.55	-0.47	0.35
CMA	3.73	2.37	-7.65	8.45	8.33	1.82	0.06	0.45
CMA*	4.89	2.60	-8.04	8.64	9.91	0.11	-0.06	0.49
Asia Pacific ex Japan (2014:11 - 2020:04)								
RMRF	-0.68	-0.10	-19.06	11.13	16.52	3.46	-0.92	-0.04
RMRF*	-3.06	-0.34	-25.49	9.56	21.10	3.59	-1.31	-0.15

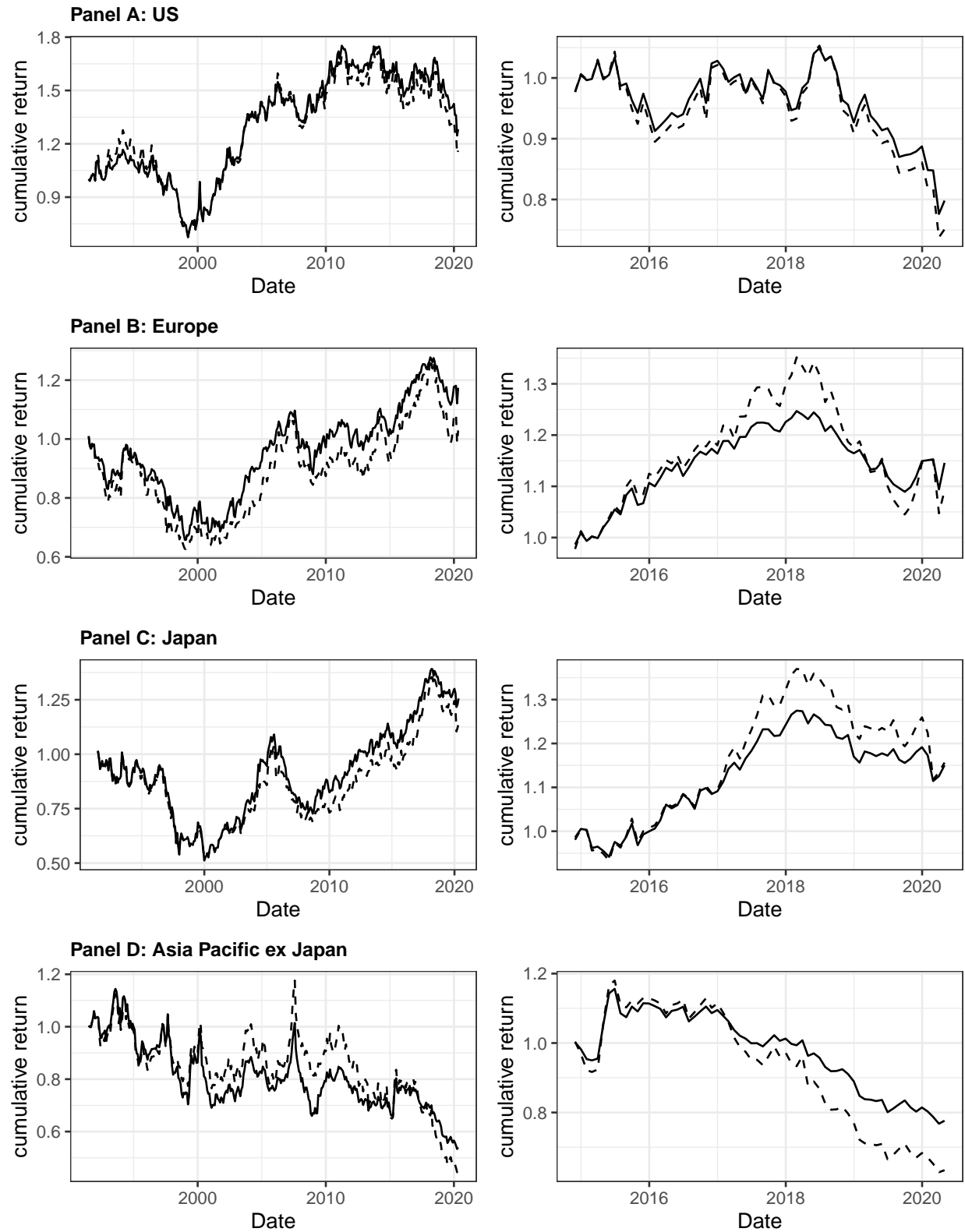
SMB	-4.15	-1.14	-6.10	10.24	8.69	6.02	1.53	-0.48
SMB*	-7.30	-1.47	-8.82	14.47	12.07	5.55	1.37	-0.60
HML	2.10	0.68	-5.85	4.36	7.20	-0.04	-0.55	0.29
HML*	3.89	0.88	-6.71	7.00	10.24	-0.38	-0.35	0.38
RMW	4.55	1.53	-6.26	6.46	6.81	2.64	-0.33	0.67
RMW*	6.97	1.70	-7.70	7.69	9.35	1.36	-0.37	0.75
CMA	0.74	0.39	-3.58	2.74	4.41	0.48	-0.24	0.17
CMA*	1.71	0.43	-7.14	5.96	9.15	0.20	-0.04	0.19

This table compares the performance statistics of the risk-managed factor strategies in the four regions US, Europe, Japan and Asia Pacific ex Japan over the full sample period (1990:06 - 2020:04) and after the study from Barroso and Santa-Clara (2015) has been published (2014:11 - 2020:04). The risk-managed factor strategies use the monthly realized variance based on the previous 126 trading days (six months) and a target volatility to scale the exposure to the respective factor. The target volatility is set to 15 per cent p.a. for the market factor (RMRF) and nine per cent p.a. for the size (SMB), value (HML), profitability (RMW) and investment (CMA) factor. Monthly realized variances are defined as the sum of squared daily returns in the previous 126 trading days, divided by 126 and then multiplied by 21 to get a monthly variance forecast. Daily and monthly returns for the risk factors are from Kenneth French' website.



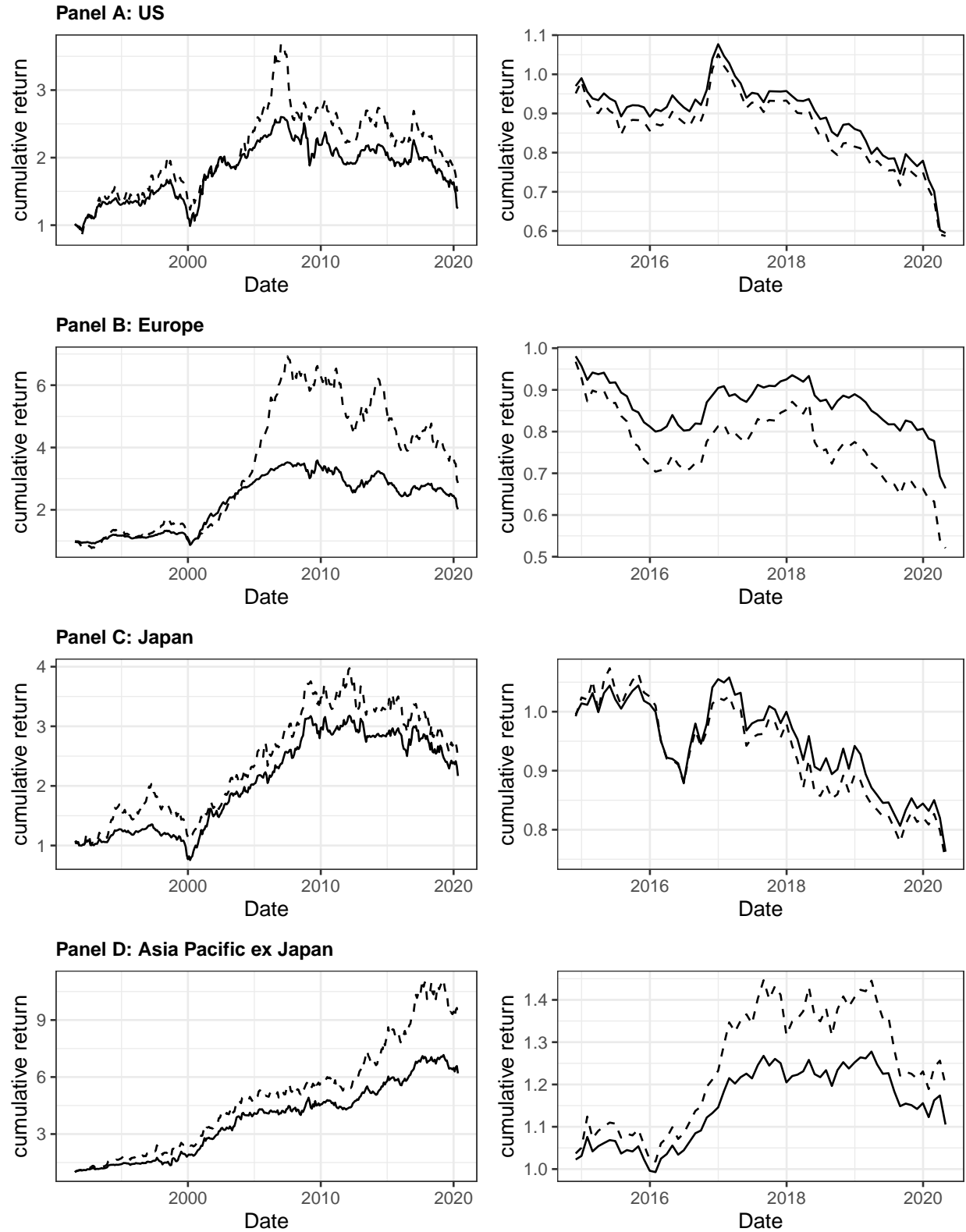
This figure plots the cumulative return of the standard (straight line) and risk-managed (dashed) market strategy RMRF in the four regions US, Europe, Japan and Asia Pacific ex Japan. The risk-managed market strategy uses the monthly realized variance based on the previous 126 trading days (six months) and a target volatility of 12 per cent p.a. to scale the exposure to the market factor RMRF. Monthly realized variances are defined as the sum of squared daily returns in the previous 126 trading days, divided by 126 and then multiplied by 21 to get a monthly variance forecast. The plots on the left-hand side show the cumulative return for the full sample period from 1990:06 to 2020:04 (347 months). The plots on the right-hand side show the cumulative return for the recent sample period from 2014:11 to 2020:04 (66 months) after the study from Barroso and Santa-Clara (2015) has been published. Daily and monthly returns for the market factor are from Kenneth French' website.

Figure 13: Risk-managed market (RMRF) strategy



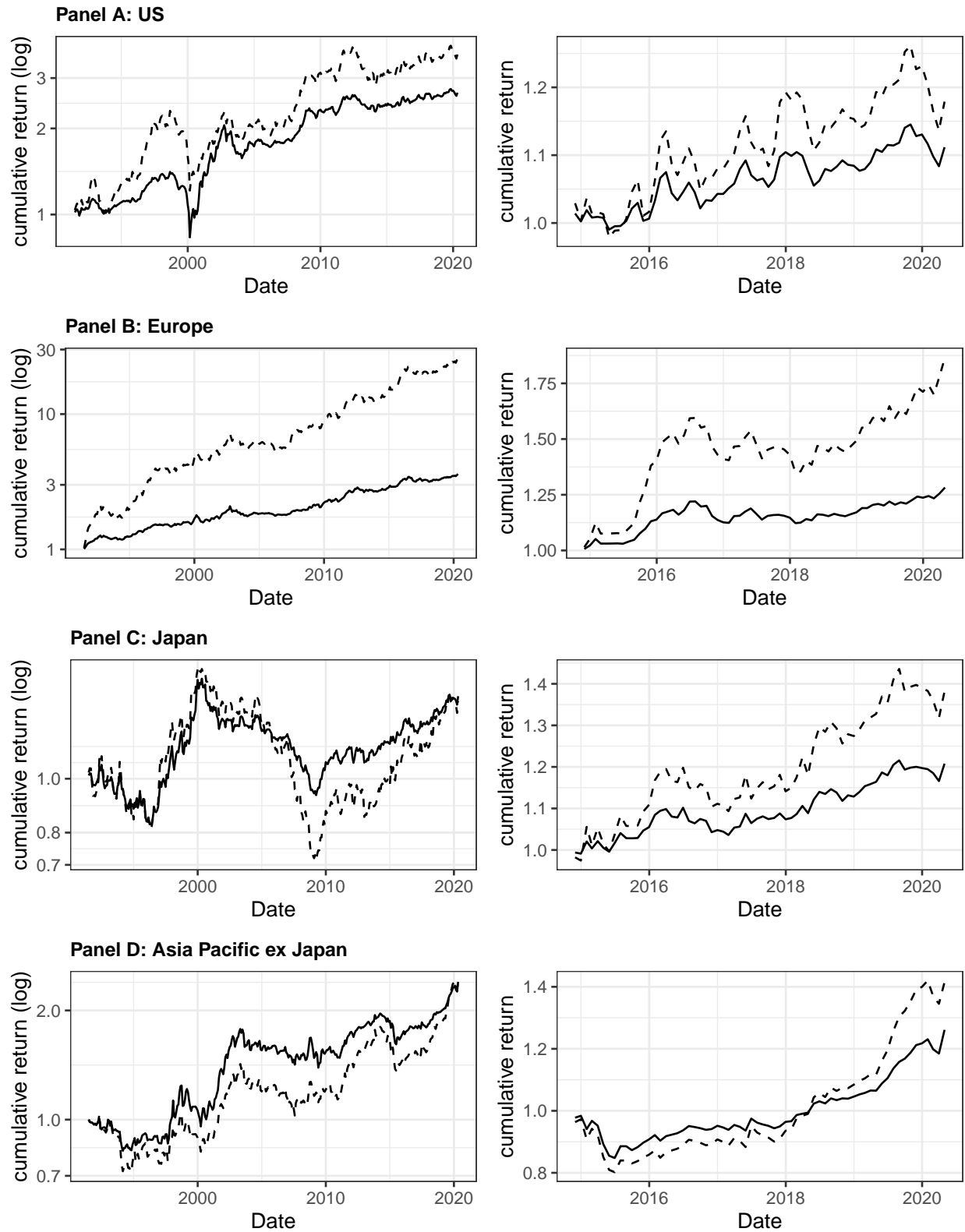
This figure plots the cumulative return of the standard (straight line) and risk-managed (dashed) size strategy SMB in the four regions US, Europe, Japan and Asia Pacific ex Japan. The risk-managed size strategy uses the monthly realized variance based on the previous 126 trading days (six months) and a target volatility of nine per cent p.a. to scale the exposure to the size factor SMB. Monthly realized variances are defined as the sum of squared daily returns in the previous 126 trading days, divided by 126 and then multiplied by 21 to get a monthly variance forecast. The plots on the left-hand side show the cumulative return for the full sample period from 1990:06 to 2020:04 (347 months). The plots on the right-hand side show the cumulative return for the recent sample period from 2014:11 to 2020:04 (66 months) after the study from Barroso and Santa-Clara (2015) has been published. Daily and monthly returns for the size factor are from Kenneth French' website.

Figure 14: Risk-managed size (SMB) strategy



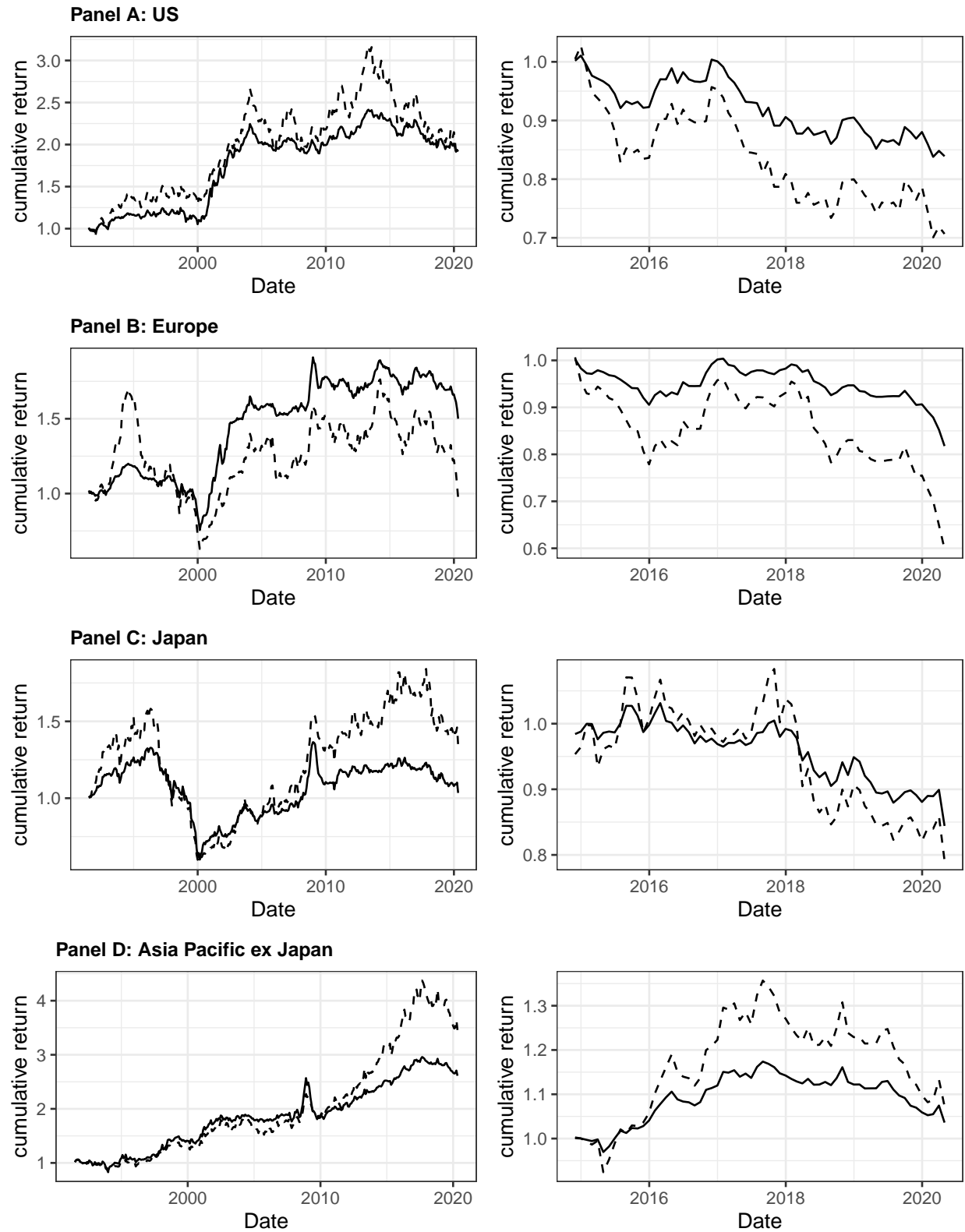
This figure plots the cumulative return of the standard (straight line) and risk-managed (dashed) value strategy HML in the four regions US, Europe, Japan and Asia Pacific ex Japan. The risk-managed value strategy uses the monthly realized variance based on the previous 126 trading days (six months) and a target volatility of nine per cent p.a. to scale the exposure to the value factor HML. Monthly realized variances are defined as the sum of squared daily returns in the previous 126 trading days, divided by 126 and then multiplied by 21 to get a monthly variance forecast. The plots on the left-hand side show the cumulative return for the full sample period from 1990:06 to 2020:04 (347 months). The plots on the right-hand side show the cumulative return for the recent sample period from 2014:11 to 2020:04 (66 months) after the study from Barroso and Santa-Clara (2015) has been published. Daily and monthly returns for the value factor are from Kenneth French' website.

Figure 15: Risk-managed value (HML) strategy



This figure plots the cumulative return of the standard (straight line) and risk-managed (dashed) profitability strategy RMW (winners–minus–losers) in the four regions US, Europe, Japan and Asia Pacific ex Japan. The risk-managed profitability strategy uses the monthly realized variance based on the previous 126 trading days (six months) and a target volatility of nine per cent p.a. to scale the exposure to the profitability factor RMW. Monthly realized variances are defined as the sum of squared daily returns in the previous 126 trading days, divided by 126 and then multiplied by 21 to get a monthly variance forecast. The plots on the left-hand side show the cumulative return for the full sample period from 1990:06 to 2020:04 (347 months). The plots on the right-hand side show the cumulative return for the recent sample period from 2014:11 to 2020:04 (66 months) after the study from Barroso and Santa-Clara (2015) has been published. Daily and monthly returns for the profitability strategies are from Kenneth French's website.

Figure 16: Risk-managed profitability (RMW) strategy



This figure plots the cumulative return of the standard (straight line) and risk-managed (dashed) investment strategy CMA in the four regions US, Europe, Japan and Asia Pacific ex Japan. The risk-managed investment strategy uses the monthly realized variance based on the previous 126 trading days (six months) and a target volatility of 12 per cent p.a. to scale the exposure to the investment factor CMA. Monthly realized variances are defined as the sum of squared daily returns in the previous 126 trading days, divided by 126 and then multiplied by 21 to get a monthly variance forecast. The plots on the left-hand side show the cumulative return for the full sample period from 1990:06 to 2020:04 (347 months). The plots on the right-hand side show the cumulative return for the recent sample period from 2014:11 to 2020:04 (66 months) after the study from Barroso and Santa-Clara (2015) has been published. Daily and monthly returns for the investment factor are from Kenneth French' website.

Figure 17: Risk-managed investment (CMA) strategy

4.5 Chapter Conclusion

Existing research, such as that by Barroso & Santa-Clara (2015), reveals that the distribution of equity momentum returns is highly negatively skewed with large drawdowns. However, it also demonstrates that the risk of momentum is highly predictable in the United States. In this paper we reveal that the risk of momentum is not only predictable in the U.S. but also in all other developed market equity regions, in other words Europe, Japan, and the Asia Pacific region excluding Japan. Further, we demonstrate that the predictability of the variance is not unique to the momentum strategy but rather is a common characteristic that applies to all five Fama and French factors, market (RMRF), size (SMB), value (HML), profitability (RMW), and investments (CMA). We find that the risk of the investment factor, which is not included in the analysis of Barroso & Santa-Clara (2015), and the value factor reveal an ever higher persistence than momentum, on average, across the four regions. Additionally, the persistence in risk varies substantially by region: The AR(1) coefficients across all six strategies average approximately 0.66 in both the U.S. and Europe, 0.55 in Japan, and only 0.48 in the Asia Pacific ex Japan region. We further indicate that a risk-managed investment strategy based on an AR(1) volatility forecast and a volatility target approach substantially improves the risk-return profile of the momentum strategy, mainly by improving the skewness and kurtosis and thus reducing its crash risk. However, the same strategy fails to improve the risk-return profile for the other risk factors despite the high predictability of their risk. Decomposing the risk of momentum reveals that the vast majority of the risk is strategy-specific and not driven by the variance of the broad stock market. This might explain the success of the risk-managed strategy for momentum.

Importantly, the time series of the variance of momentum strategies and its residuals from AR(1) first-order AR models are highly autocorrelated. Thus, as opposed to Barroso & Santa-Clara (2015), our empirical results are based on heteroskedasticity- and autocorrelation-consistent (HAC) standard errors to circumvent this issue.

We demonstrate that the high autocorrelation of momentum risk is limited not only to the first lag but is statistically significant for up to approximately 10 lags based on monthly data. Thus, future research might expand the set of autocorrelation coefficients included in the analysis to further improve the variance forecast of momentum. Furthermore, as we have shown in Section 4.4.2.1, the variance of the broad stock market also has some explanatory power for the contemporaneous variance of momentum. To further improve the variance forecast of momentum future research might analyse the relationship between the future variance of momentum and past stock market variance.

5 Conclusion

In Chapter 2 (Blankenburg (2021a)) we examine how firm characteristics contribute to the empirical finding that analyst earnings forecasts are too optimistic. We focus on firm characteristics that underlie popular risk-factor models with a focus on investment and profitability measures, as they are the main drivers of the cross-section of expected returns (Hou et al., 2017).

Overall, our results emphasise the role of information uncertainty when estimating the value of a firm. According to Zhang (2006) information uncertainty can potentially stem from two sources: volatility of a firm's underlying fundamentals and poor information. Based on this, he argues that high-uncertainty stocks are likely to be growth stocks. Moreover, as small firms have less information available to the market, he uses firm size as one proxy for information uncertainty. In line with that, we find that growth stocks and, to a lesser extent, also small-cap stocks have a higher volatility in their investment and profitability measures in addition to more volatile returns. Furthermore, we document that small-growth stocks have the most negative and most volatile earnings forecast errors. Based on panel regressions, we further provide evidence that measures of corporate investments are negatively related to future earnings forecast errors. This implies that higher investments (specifically measured via Investment-to-Capital) lead to either lower actual earnings in the next period, higher estimated earnings for the next period, or a combination of the two. Higher profitability, measured as Operating Profitability and Return-on-Equity, has the opposite effect and leads to improved earnings forecast errors. When comparing the results for portfolios of value and growth stocks, we find that the magnitude of the coefficients for the investment and profitability measures is more pronounced for growth stocks. Additionally, the tested corporate fundamentals explain a much higher variance of the earnings forecast errors of growth stocks compared to value stocks.

To our best knowledge, we contribute to the literature the first study that directly links the

properties of earnings forecast errors to corporate fundamentals underlying the risk-factors in the most important factor models for the cross-section of stock returns. Moreover, our findings provide further evidence on the role of information uncertainty, potentially caused by volatility in a firm's underlying fundamentals and poor information, in evaluating a company's value in light of new information. Thus, the presented evidence also provides new insights into the underlying cause of the value effect. We conclude that mispricing in the form of earnings forecast errors should be taken into account when analysing the value effect.

Existing research, such as that conducted by Stambaugh & Yuan (2017), show that factor models can be useful to examine whether expected returns reflect some sort of risk or mispricing. Factors may capture systematic risk where investors demand a risk premium as compensation for bearing that risk, or factors can capture sources of mispricing, such as investor sentiment or uncertainty related to earnings. In Chapter 3 (Blankenburg (2021b)) we examine how uncertainty around earnings as proxied by earnings forecast errors, which we introduced in Chapter 2, contribute to the mispricing phenomenon. We focus on the Fama & French (2015) five-factor model, the Carhart (1997) four-factor model, and the Hou et al. (2015) q -factor model, as they largely summarise the cross-section of average stock returns. Moreover, we add earnings forecast errors to the four-factor model of Stambaugh & Yuan (2017), which includes two mispricing factors.

We find that, when significant, the coefficient for earnings forecast errors is always strongly positive, which is mostly the case for large-cap portfolios. This implies that less mispricing in the form of less negative earnings forecast errors corresponds to higher contemporaneous returns. Adding earnings forecast errors to existing risk-factor models also lowers the estimated betas of the market excess return and the value risk factor (HML) for value stocks in all tested models. Therefore, our results suggest that some of the perceived general stock market risk and the value premium might instead be uncertainty regarding earnings as measured by earnings forecast errors. Furthermore, when added to the Stambaugh & Yuan (2017)

four-factor model, earnings forecast errors are the most significant mispricing factor among the three included, by far. Thus, we contribute evidence that earnings forecast errors capture a distinctively different mispricing aspect not captured by the other two mispricing factors, namely, uncertainty regarding earnings. Overall, adding earnings forecast errors to existing risk-factor models significantly raises the portion of variability explained in the returns of the 25 size- and book-to-market sorted portfolios in all four tested models. Thus, we conclude that the more complex models including earnings forecast errors are significantly better at explaining portfolio returns.

Chapter 4 (Blankenburg (2021c)) looks at the risk of equity momentum strategies. Previous literature, such as that of Barroso & Santa-Clara (2015), documents that the distribution of equity momentum returns is highly negatively skewed with large drawdowns. But they also show that the risk of momentum is highly predictable. However, most papers study this phenomenon only for the U.S. market or selected European countries. Our contribution is that we extend the previous studies to a larger sample and show that the risk of momentum is not only predictable in the U.S. but also in all other developed market equity regions - Europe, Japan, and the Asia Pacific region excluding Japan. Further, we provide evidence that the predictability of the variance is not unique to the momentum strategy but rather a common characteristic that applies to all five Fama and French factors - market excess return (RMRF), size (SMB), value (HML), profitability (RMW) and investments (CMA).

We further contribute that a risk-managed investment strategy based on an AR(1) volatility forecast and a volatility target approach substantially improves the risk-return profile of the momentum strategy in all developed market regions, mainly by improving the skewness and kurtosis and thus reducing its crash risk. The risk-managed strategy remains successful after it was first proposed by Barroso & Santa-Clara (2015). However, we document that the same strategy fails to improve the risk-return profile for the other risk factors despite the high predictability of their risk. Decomposing the risk of momentum shows that the vast

majority of the risk is strategy-specific and is not driven by the variance of the broad stock market. Thus, we conclude that this might explain the success of the risk-managed strategy for momentum.

In sum, this dissertation sheds fresh and new light on earnings forecast errors and the risk of momentum. The presented empirical findings highlight the importance of understanding the driving forces behind earnings forecast errors based on their broad empirical power in explaining the cross-section of stock returns. Regarding Chapter 2, the provided results deserve further investigation on a broader set of company characteristics and whether the documented findings can be confirmed outside the United States. Regarding Chapter 3, future research might expand on the set of mispricing factors to examine their interaction with earnings forecast errors and analyse earnings forecast errors over various horizons. Finally, in Chapter 4, we demonstrate that the high autocorrelation of momentum risk is limited not only to the first lag but is statistically significant for up to approximately 10 lags based on monthly data. Therefore, an important avenue for future research is to expand the set of autocorrelation coefficients included in the analysis to further improve the variance forecast.

A Appendix to Chapter 3: Full Regression Details

Table 19: Summary statistics for Fama-French five-factor model

	11	12	13	14	15	21	22	23	24	25	31	32	33	34	35	41	42	43	44	45	51	52	53	54	55
(Intercept)	-.00 (.01)	.05* (.02)	.03 (.02)	.02 (.02)	-.01 (.01)	-.01 (.01)	.00 (.01)	.01 (.02)	-.03** (.03)	-.04 (.03)	.00 (.01)	-.00 (.01)	-.02 (.02)	-.00 (.01)	.05** (.02)	.04* (.02)	-.00 (.01)	.00 (.01)	-.01 (.01)	-.01 (.02)	.02 (.01)	-.02 (.01)	.00 (.01)	-.03 (.02)	.03 (.03)
MKT-RF	1.08*** (.10)	.88*** (.08)	.97*** (.08)	1.11*** (.08)	1.13*** (.08)	1.05*** (.07)	1.01*** (.06)	1.04*** (.08)	1.06*** (.05)	1.14*** (.13)	.99*** (.11)	1.15*** (.05)	1.05*** (.05)	.99*** (.12)	.81*** (.11)	.84*** (.11)	.98*** (.08)	.90*** (.07)	1.02*** (.08)	1.07*** (.08)	1.00*** (.05)	1.07*** (.06)	.88*** (.05)	1.00*** (.04)	.77*** (.12)
SMB	1.61*** (.15)	1.49*** (.18)	1.61*** (.12)	1.49*** (.12)	1.32** (.08)	1.05*** (.07)	.96*** (.08)	1.34*** (.14)	.74*** (.09)	.99*** (.14)	.88*** (.23)	.90*** (.08)	.80*** (.07)	.71** (.21)	.86*** (.14)	.67*** (.15)	.44*** (.09)	.68*** (.13)	.61*** (.11)	.22 (.21)	-.26* (.11)	-.27** (.11)	-.11 (.09)	-.04 (.16)	.07 (.30)
HML	-.36** (.13)	-.23* (.11)	-.15 (.09)	-.06 (.13)	.32** (.09)	-.26 (.21)	.06 (.16)	.03 (.14)	.37*** (.09)	.44** (.14)	-.49*** (.12)	.00 (.10)	.35** (.10)	.33** (.10)	.34* (.15)	-.27** (.12)	-.07 (.07)	.21 (.10)	.35* (.14)	.57*** (.14)	-.47*** (.14)	-.05 (.07)	.05 (.11)	.20 (.15)	.76 (.38)
RMW	-.55*** (.15)	-.47* (.19)	-.28 (.19)	-.09 (.17)	-.10 (.17)	.02 (.15)	.13 (.11)	.22* (.09)	.37*** (.08)	.13 (.28)	-.23 (.11)	.16 (.10)	.21 (.14)	.20 (.18)	.01 (.16)	-.26 (.14)	.13 (.12)	.06 (.14)	.29* (.13)	-.05 (.13)	.20* (.10)	.45*** (.08)	.21* (.09)	.37* (.15)	-.30 (.27)
CMA	.21 (.16)	.15 (.18)	.38* (.18)	.64** (.20)	.53* (.22)	-.17 (.31)	-.07 (.20)	-.00 (.31)	-.02 (.17)	.36 (.29)	.28 (.20)	-.01 (.20)	-.12 (.15)	.18 (.20)	.07 (.17)	-.01 (.15)	-.25 (.15)	.07 (.28)	-.06 (.15)	.58 (.33)	-.21 (.11)	.05 (.18)	-.06 (.24)	.41 (.36)	-.66 (.56)
R ²	.92	.89	.90	.90	.91	.85	.90	.91	.93	.83	.89	.94	.89	.85	.77	.88	.88	.84	.82	.78	.93	.91	.87	.79	.55
Adj. R ²	.91	.87	.88	.88	.90	.82	.88	.89	.91	.80	.87	.93	.87	.82	.73	.85	.86	.81	.79	.75	.91	.90	.84	.75	.47
Num. obs.	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34
F statistic	67.75	45.82	49.02	48.34	59.66	31.60	49.46	56.90	71.82	27.18	46.22	87.50	47.07	30.63	18.68	39.45	40.81	29.76	25.86	20.43	69.22	60.12	36.74	20.83	6.74

The table reports the summary statistics for the Fama-French five-factor model. The first number for the 25 portfolios is the book-to-market (Value) portfolio, x1 is the low book-to-market (Value) portfolio and x5 is the high low book-to-market (Value) portfolio. Times, portfolio 11 is the Small-Growth portfolio and portfolio 55 is the Large-Value portfolio. The Fama-French five-factor model is comprised of the market excess return MKT-RF, the size factor SMB, the value factor HML, the profitability factor RMW and the investment factor CMA. Test-statistics are calculated using Newey and West (1987) standard errors with four lags, which are shown in parentheses. Coefficients with $p < 0.05$ in bold, $**p < 0.01$, $***p < 0.001$. $*p < 0.05$

Table 21: Summary statistics for Carhart four-factor model

	11	12	13	14	15	21	22	23	24	25	31	32	33	34	35	41	42	43	44	45	51	52	53	54	55		
(Intercept)	-.02 (.01)	.02 (.02)	.02 (.02)	.02 (.02)	.02* (.01)	-.01 (.01)	.02 (.01)	.02 (.01)	-.02 (.01)	-.03 (.02)	-.00 (.01)	.00 (.01)	.02 (.01)	-.00 (.01)	.05*** (.01)	.02 (.02)	.02 (.01)	.00 (.01)	-.00 (.01)	.02 (.02)	.03** (.01)	.00 (.01)	.01 (.01)	.01 (.01)	-.00 (.01)	.00 (.02)	
MKT-RF	1.18*** (.08)	.95*** (.09)	.96*** (.07)	1.04*** (.06)	1.10*** (.08)	1.07*** (.10)	1.01*** (.06)	.99*** (.09)	.98*** (.04)	1.07*** (.10)	1.00*** (.10)	1.11*** (.06)	1.04*** (.05)	.92*** (.09)	.80*** (.10)	.89*** (.12)	.93*** (.06)	.88*** (.06)	.96*** (.08)	1.03*** (.08)	.93*** (.05)	.98*** (.06)	.84*** (.05)	.89*** (.08)	.80*** (.16)	.90*** (.31)	
SMB	1.67*** (.17)	1.51*** (.17)	1.69*** (.11)	1.63*** (.13)	1.47*** (.13)	1.01*** (.08)	.96*** (.08)	1.35*** (.17)	.74*** (.08)	1.09*** (.17)	.94*** (.22)	.89*** (.09)	.79*** (.11)	.75*** (.18)	.88*** (.15)	.65*** (.18)	.52*** (.09)	.69*** (.09)	.59*** (.13)	.39 (.20)	-.21 (.14)	-.25*** (.06)	-.13 (.06)	.16 (.17)	-.11 (.31)	-.11 (.31)	
HML	-.50*** (.11)	-.33** (.10)	-.07 (.09)	20* (.08)	.47*** (.05)	-.32* (.12)	.05 (.10)	.11 (.09)	.53*** (.10)	.11 (.09)	-.45*** (.08)	.07 (.05)	.36*** (.09)	.49*** (.08)	.38*** (.10)	-.37** (.10)	.07 (.08)	.27*** (.06)	.46** (.13)	.76*** (.10)	-.30*** (.08)	.14 (.12)	.12 (.10)	.12 (.10)	.50** (.16)	.38** (.14)	.38** (.14)
WML	-.06 (.09)	.09 (.09)	.15 (.09)	.21* (.09)	-.01 (.06)	-.04 (.11)	-.12 (.08)	-.00 (.07)	-.06 (.06)	.05 (.06)	.07 (.05)	.05 (.09)	-.10 (.08)	-.08 (.06)	-.04 (.07)	.02 (.06)	-.02 (.08)	.05 (.11)	.06 (.11)	.06 (.13)	-.01 (.06)	.07 (.04)	-.01 (.05)	.04 (.08)	.02 (.14)	-.08 (.24)	-.08 (.24)
R ²	.90	.87	.90	.90	.90	.85	.91	.90	.90	.82	.89	.94	.89	.84	.77	.86	.87	.84	.81	.76	.92	.87	.86	.73	.50	.73	.50
Adj. R ²	.89	.85	.88	.89	.89	.83	.89	.89	.89	.80	.87	.93	.88	.82	.74	.84	.85	.82	.78	.73	.90	.85	.84	.70	.43	.70	.43
Num. obs.	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34
F statistic	65.23	48.06	61.97	64.60	66.28	40.66	69.36	67.45	68.06	33.13	56.13	109.04	60.34	37.62	24.35	45.66	47.64	38.94	30.87	23.56	78.57	46.56	43.02	43.02	19.91	7.22	7.22

The table tests the ability of the Carhart four-factor model to explain annual excess returns on 25 portfolios formed on size and book-to-market for the 34 portfolios formed on July of year t to June of year t+1, and the portfolios are rebalanced at the end of June t+1. Risk factor returns are aligned with portfolio returns and calculated from July of year t to June of year t+1. The first number for the 25 size and book-to-market portfolios represents the size portfolio, 1x is the small market capitalisation portfolio, 5x is the large capitalisation portfolio. The second number represents the book-to-market portfolio: x1 is the low book-to-market (Value) portfolio. Thus, portfolio 11 is the Small-Growth portfolio and portfolio 55 is the Large-Value portfolio. The Carhart four-factor model is comprised of the market excess return MKT-RF, the size factor SMB, the value factor HML, and the momentum factor WML. Test-statistics are calculated using Newey and West (1987) standard errors with four lags, which are shown in parentheses. Coefficients with $p < 0.05$ in bold, $**p < 0.01$, $***p < 0.001$.

Table 22: Summary statistics for Carhart four-factor model and earnings forecast errors

	11	12	13	14	15	21	22	23	24	25	31	32	33	34	35	41	42	43	44	45	51	52	53	54	55
(Intercept)	-.05	.01	.05	.03	.08***	.00	.03	.04	-.02	.01	.04*	.01	.01	.04*	.09***	.07***	.03	.02	.05	.02*	.01	.01	.02*	.02	.02
MKT-RF	1.20***	.95***	.94***	1.02***	1.03***	1.05***	.99***	.98***	.98***	1.04***	.92***	1.09***	1.02***	.87***	.71***	.83***	.90***	.85***	.92***	.97***	.96***	.97***	.82***	.84***	.89***
SMB	1.69***	1.51***	1.68***	1.62***	1.40***	1.03***	.97***	1.34***	.74***	1.10***	.94***	.89***	.77***	.73***	.82***	.72***	.52***	.66***	.59***	.48*	-.24	-.25***	-.10	.19	-.08
HML	-.51***	-.33**	-.10	.19*	.40***	-.31*	.06	.10	.54***	.59***	-.39***	.07	.35**	.42***	.35**	-.35***	.06	.25**	.40**	.66***	.13	.07	.45*	.38**	.30
WML	-.07	.09	.15	.21*	-.03	-.01	-.12	-.01	.06	.02	.09*	.05	-.10	.05	-.01	.03	-.03	-.04	.08*	.01	.02	-.01	-.00	-.09	-.09
EFE	-.66	-.49	1.77	.95	4.91*	.74	1.38	1.37	-.66	3.77	2.71**	.91	2.90*	4.89***	8.18***	5.30***	3.71	5.24**	3.55*	3.59*	.53	3.60***	6.60***	8.40	
	(1.07)	(1.26)	(2.15)	(1.85)	(1.80)	(.79)	(.98)	(1.90)	(1.72)	(3.33)	(.78)	(.78)	(1.21)	(1.25)	(1.47)	(1.05)	(1.84)	(1.78)	(1.49)	(1.59)	(1.40)	(.79)	(.80)	(1.74)	(8.40)
R ²	.90	.87	.90	.90	.92	.85	.91	.90	.90	.83	.91	.94	.90	.86	.84	.91	.88	.87	.82	.78	.92	.87	.88	.77	.53
Adj. R ²	.88	.85	.88	.88	.90	.82	.89	.89	.89	.80	.89	.93	.88	.84	.81	.89	.86	.85	.79	.74	.90	.84	.85	.73	.44
Num. obs.	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34
F statistic	51.33	37.25	48.95	50.16	60.79	31.73	55.61	53.02	52.78	26.83	56.57	85.24	51.02	34.63	28.65	56.10	42.64	38.96	25.44	20.21	63.12	36.10	39.53	18.71	6.29

The table tests the ability of the Carhart four-factor model including earnings forecast errors to explain annual excess returns on 25 portfolios formed on size and book-to-market for the 31 portfolio formation years from 1982-2015. The value-weighted excess portfolio returns are calculated from July of year t to June of t+1, and the portfolios are rebalanced at the end of June t+1. Risk factor returns are aligned with portfolio returns and calculated from July of year t to June of t+1. The first number for the 25 size and book-to-market portfolios represents the size portfolio, 1x is the small market capitalisation portfolio, 5x is the large capitalisation portfolio. The second number represents the book-to-market portfolio; x1 is the low book-to-market (Value) portfolio, 5x is the high low book-to-market (Value) portfolio. Thus, portfolio 11 is the SmallGrowth portfolio and portfolio 35 is the Large Value portfolio. The Carhart four-factor model is comprised of the market excess return, MKT-RF, SMB, HML, and WML. The earnings forecast errors are calculated using Newey and West (1987) standard errors with four lags, which are shown in parentheses. Coefficients with $p < 0.05$ in **bold**, $***p < 0.001$, $**p < 0.01$, $*p < 0.05$ scaled by total assets per share in year t. Earnings forecast errors are estimated every year at the 1 per cent and 99 per cent levels. Test statistics are calculated using Newey and West (1987) standard errors with four lags, which are shown in parentheses. Coefficients with $p < 0.05$ in **bold**, $***p < 0.001$, $**p < 0.01$, $*p < 0.05$

Table 23: Summary statistics for Hou q-factor model

	11	12	13	14	15	21	22	23	24	25	31	32	33	34	35	41	42	43	44	45	51	52	53	54	55
(Intercept)	.01 (.01)	.05* (.02)	.04 (.02)	.02 (.02)	.00 (.02)	-.01 (.01)	.00 (.01)	.01 (.02)	-.04* (.02)	-.05 (.03)	.02 (.01)	-.00 (.01)	-.03 (.02)	-.01 (.02)	.04** (.01)	.05* (.02)	.00 (.01)	-.00 (.02)	-.02 (.02)	-.01 (.02)	.03 (.02)	-.02 (.01)	.00 (.01)	-.04 (.02)	.01 (.02)
MKT-RF	1.06*** (.13)	.87*** (.09)	.96*** (.09)	1.11*** (.08)	1.15*** (.11)	1.03*** (.09)	1.01*** (.07)	1.04*** (.08)	1.08*** (.08)	1.17*** (.15)	.97*** (.11)	1.15*** (.05)	1.07*** (.07)	1.00*** (.13)	.83*** (.14)	.82*** (.12)	.97*** (.08)	.91*** (.08)	1.04*** (.09)	1.10*** (.11)	.97*** (.07)	1.07*** (.06)	.88*** (.04)	1.02*** (.08)	.81*** (.10)
SMB	1.66*** (.20)	1.53*** (.20)	1.64*** (.14)	1.50*** (.13)	1.27*** (.18)	1.09*** (.20)	.95*** (.08)	1.34*** (.14)	.69*** (.12)	.92*** (.14)	.95*** (.27)	.90*** (.08)	.75*** (.09)	.66*** (.23)	.81*** (.18)	.71*** (.18)	.45*** (.09)	.65*** (.13)	.56*** (.13)	.13 (.18)	-.19 (.17)	-.26* (.09)	-.12 (.08)	-.01 (.14)	-.04 (.25)
RMW	-.67*** (.15)	-.56* (.21)	-.33 (.21)	-.11 (.18)	.02 (.19)	-.07 (.15)	.15 (.10)	.24* (.10)	.51*** (.12)	.29 (.32)	-.41* (.16)	.16 (.10)	.34 (.18)	.32* (.13)	.13 (.11)	-.36* (.15)	.10 (.12)	.13 (.12)	.42** (.13)	.16 (.19)	.03 (.14)	.43*** (.06)	.23** (.07)	.44* (.16)	-.02 (.30)
CMA	-.19 (.18)	-.10 (.17)	.21 (.19)	.58*** (.16)	.88*** (.20)	-.45 (.25)	.00 (.10)	.03 (.19)	.43** (.14)	.84** (.30)	-.26 (.20)	-.01 (.15)	.26* (.13)	.54** (.19)	.44** (.13)	-.31 (.18)	.18 (.09)	.29 (.22)	.33 (.20)	1.21*** (.28)	-.31* (.14)	-.01 (.09)	-.00 (.16)	.64* (.24)	.17 (.36)
R ²	.91	.88	.89	.90	.90	.84	.90	.91	.89	.80	.85	.94	.86	.82	.74	.86	.88	.83	.79	.72	.87	.91	.87	.78	.42
Adj. R ²	.90	.87	.88	.88	.88	.82	.88	.90	.88	.77	.83	.93	.85	.79	.70	.84	.86	.81	.76	.68	.85	.90	.85	.74	.34
Num. obs.	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34
F statistic	71.48	54.47	61.01	62.24	64.34	37.49	63.39	73.53	60.46	28.61	40.96	113.28	46.05	32.52	20.33	43.65	52.08	35.07	27.32	18.58	47.53	76.93	47.12	25.09	5.25

The table tests the ability of the Hou q-factor model to explain annual excess returns on 26 portfolios formed on size and book-to-market for the 34 portfolio formation years from 1982-2015. The value-weighted excess portfolio returns are calculated from July of year t to June of t+1, and the portfolios are evaluated at the end of June t+1. Risk factor returns are aligned with portfolio returns and calculated from July of year t to June of t+1. The first number for the 25 size and book-to-market portfolios represents the size portfolio, 1x is the small market capitalisation portfolio, 5x is the large capitalisation portfolio. The second number represents the book-to-market portfolio, x1 is the low book-to-market (Growth) portfolio and x5 is the high low book-to-market (Value) portfolio. Thus, portfolio 1x is the Small-Growth portfolio and portfolio 5x is the Large-Value portfolio. The Hou q-factor model is comprised of the market excess return MKT-RF, the size factor SMB, the profitability factor RMW and the investment factor CMA. Test-statistics are calculated using Newey and West (1987) standard errors with four lags, which are shown in parentheses. Coefficients with $p < 0.05$ in bold, $**p < 0.01$, $***p < 0.001$.

Table 24: Summary statistics for Hou q-factor model and earnings forecast errors

	11	12	13	14	15	21	22	23	24	25	31	32	33	34	35	41	42	43	44	45	51	52	53	54	55	
(Intercept)	-01	.02	.04	.03	.08***	.01	.02	.03	-.02	-.01	.05*	.01	.00	.03*	.08***	.07**	.02	.02	.02	.03	.03	-.01	.01	.01	-.01	.02
MKT-RF	.03	.03	.02	.03	.02	.01	.02	.02	.03	.04	.02	.01	.02	.01	.01	.02	.01	.02	.02	.03	.02	.01	.01	.01	.03	.03
	1.07***	.88***	.96***	1.09***	1.06***	1.03***	1.00***	1.01***	1.06***	1.12***	.93***	1.12***	1.06***	.95***	.75***	.81***	.96***	.89***	.96***	1.02***	.98***	1.05***	.87***	.96***	.82***	.87***
SMB	1.68***	1.55***	1.64***	1.49***	1.16***	1.11***	.94***	1.32***	.69***	.94***	.94***	.91***	.72***	.64***	.79***	.75***	.44***	.60***	.61***	.31	-.20	-.27***	-.11	.06	-.05	-.05
	(.21)	(.21)	(.14)	(.13)	(.15)	(.20)	(.10)	(.16)	(.11)	(.14)	(.24)	(.08)	(.06)	(.18)	(.14)	(.17)	(.11)	(.11)	(.09)	(.19)	(.16)	(.08)	(.08)	(.14)	(.27)	(.27)
RMW	-.66***	-.57**	-.33	-.10	.02	-.06	.19*	.27*	.54***	.26	-.30	.21*	.47*	.42***	.35***	-.24	.18	.23	.52**	.25	.02	.44***	.22**	.52**	.03	.03
	(.14)	(.19)	(.23)	(.18)	(.18)	(.15)	(.08)	(.10)	(.14)	(.30)	(.20)	(.10)	(.18)	(.11)	(.08)	(.17)	(.10)	(.13)	(.17)	(.20)	(.14)	(.06)	(.06)	(.16)	(.32)	(.32)
CMA	-.20	-.13	.21	.55***	.81**	-.44	.02	.00	.40**	.81**	-.22	-.04	.20*	.37*	.22	-.32	.15	.25	.10	.93**	-.31*	-.02	.02	.51*	.24	.24
	(.19)	(.16)	(.19)	(.15)	(.23)	(.25)	(.10)	(.18)	(.14)	(.28)	(.17)	(.15)	(.08)	(.14)	(.14)	(.17)	(.09)	(.18)	(.22)	(.33)	(.14)	(.09)	(.13)	(.23)	(.24)	(.24)
EFE	-.44	-.166	.30	1.02	6.58***	.54	2.05	2.37	2.76	4.33	2.33*	2.14	5.34*	7.63***	9.60***	4.11*	4.62***	6.52**	4.70***	6.85**	-.52	1.44	3.63***	8.45**	8.95	8.95
	(.88)	(1.39)	(1.72)	(1.34)	(1.30)	(.47)	(1.08)	(2.12)	(2.02)	(2.60)	(1.06)	(1.10)	(1.94)	(1.60)	(1.30)	(1.68)	(1.10)	(2.09)	(1.91)	(1.23)	(.97)	(.97)	(.68)	(2.60)	(9.65)	(9.65)
R ²	.91	.89	.89	.90	.93	.84	.90	.91	.90	.81	.87	.94	.89	.87	.82	.88	.90	.88	.83	.75	.87	.92	.89	.84	.84	.45
Adj. R ²	.89	.87	.87	.88	.91	.81	.89	.90	.88	.77	.84	.93	.87	.85	.79	.86	.88	.85	.80	.71	.84	.90	.87	.81	.81	.35
Num. obs.	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34
F statistic	55.71	43.99	47.46	48.36	71.10	29.15	52.57	60.11	50.12	23.48	36.02	93.21	44.90	39.04	25.57	41.59	51.06	39.87	27.11	16.95	36.76	62.34	46.20	28.55	4.02	4.02

The table tests the ability of the Hou q-factor model including earnings forecast errors to explain annual excess returns on 25 portfolios formed on size and book-to-market for the 34 portfolio formation years from 1982-2015. The value-weighted excess portfolio returns are calculated from July of year t to June of t+1, and the portfolios are rebalanced at the end of June t+1. Risk factor returns are aligned with portfolio returns and calculated from July of year t to June of t+1. The first number for the 25 size and book-to-market portfolios represents the size portfolio. 1x is the small market capitalisation portfolio, 5x is the large capitalisation portfolio. The second number represents the book-to-market portfolio. x1 is the low book-to-market (Value) portfolio and x5 is the high low book-to-market (Value) portfolio. Thus, portfolio 11 is the Small-Growth portfolio and portfolio 55 is the Large-Value portfolio. The Hou q-factor model is comprised of the market excess return, the market return, the book-to-market return, the size return, the growth return, and the earnings forecast error return. The earnings forecast errors are calculated using 1400 earnings announcements from July of year t to June of year t+1 scaled by total assets per share in year t. Earnings forecast errors are trimmed every year at the 1 per cent and 99 per cent levels. Test statistics are calculated using Newey and West (1987) standard errors with four lags, which are shown in parentheses. Coefficients with * p < 0.05 in bold, ** p < 0.01, *** p < 0.001.

Table 25: Summary statistics for Stambaugh and Yuan four-factor model

	11	12	13	14	15	21	22	23	24	25	31	32	33	34	35	41	42	43	44	45	51	52	53	54	55
(Intercept)	-.04	-.01	-.03	-.04*	-.01	-.04*	-.02	-.02	-.06	-.06	-.02	-.03*	-.04	-.02	.02	.03	-.01	-.02	-.04	.01	.01	-.02	-.00	-.05	.02
MKT-RF	1.23*** (.03)	1.04*** (.02)	1.10*** (.01)	1.22*** (.01)	1.09*** (.02)	1.11*** (.03)	1.07*** (.02)	1.02*** (.03)	1.04*** (.03)	1.11*** (.03)	1.08*** (.02)	1.18*** (.01)	1.02*** (.03)	.96*** (.03)	.84*** (.02)	.89*** (.03)	.97*** (.01)	.93*** (.02)	1.03*** (.03)	.98*** (.03)	1.04*** (.02)	1.04*** (.02)	.88*** (.01)	.99*** (.03)	.79*** (.04)
SMBn	1.70*** (.19)	1.56*** (.19)	1.74*** (.19)	1.71*** (.14)	1.58*** (.17)	1.06*** (.14)	.96*** (.13)	1.38*** (.19)	.73*** (.15)	1.17*** (.14)	.96*** (.22)	.90*** (.11)	.85*** (.10)	.76*** (.22)	.92*** (.16)	.65*** (.16)	.52*** (.10)	.78*** (.11)	.57*** (.17)	.48*** (.19)	-.20 (.14)	-.28*** (.08)	-.16 (.16)	.07 (.29)	-.16 (.29)
MGMNT	-.53** (.18)	-.38* (.14)	-.13 (.12)	.16 (.12)	.23 (.13)	-.41*** (.10)	.02 (.13)	.00 (.13)	.43* (.18)	.41 (.20)	-.50*** (.16)	-.02 (.08)	.21 (.19)	.30 (.16)	.24 (.13)	-.48*** (.13)	.03 (.11)	.12 (.11)	.33 (.20)	.54* (.20)	-.13 (.09)	.23* (.10)	.11 (.13)	.49* (.22)	.12 (.25)
PERF	-.01 (.06)	.05 (.07)	.09 (.07)	.11 (.06)	-.11 (.08)	.10 (.05)	-.00 (.05)	.09 (.05)	.07 (.07)	.11 (.11)	.12* (.05)	.09 (.07)	-.02 (.07)	.05 (.07)	.03 (.07)	.03 (.07)	.06 (.04)	.08 (.04)	.13 (.10)	.13* (.09)	-.11 (.09)	.13* (.06)	.12* (.05)	.20* (.09)	-.08 (.19)
R ²	.86	.84	.86	.87	.81	.86	.87	.87	.79	.70	.87	.92	.81	.70	.68	.86	.86	.81	.72	.61	.88	.88	.87	.68	.43
Adj. R ²	.85	.82	.84	.85	.78	.84	.85	.85	.76	.66	.86	.91	.78	.66	.64	.84	.84	.78	.68	.56	.87	.87	.85	.64	.35
Num. obs.	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34
F statistic	46.23	37.80	43.54	48.46	30.91	44.52	46.80	48.21	26.68	16.74	50.67	82.51	31.02	16.98	15.59	44.30	43.76	30.34	18.60	11.33	55.35	54.97	46.67	15.64	5.49

The table tests the ability of the Stambaugh and Yuan four-factor model to explain annual excess returns on 26 portfolios formed on size and book-to-market for the 34 portfolio formation years from 1982-2016. The value-weighted excess portfolio returns are calculated from July of year t to June of t+1, and the portfolios are rebalanced at the end of June t+1. Risk factor returns are aligned with portfolio returns and calculated from July of year t to June of t+1. The first number for the 25 size and book-to-market portfolios represents the size portfolio. 1x is the small market capitalisation portfolio, 5x is the large capitalisation portfolio. The second number for the 26 portfolios is the high low book-to-market portfolio. 11 is the high book-to-market portfolio and 25 is the low book-to-market portfolio. Coefficients are in bold. Coefficients in parentheses are t-statistics. Standard errors are in parentheses. The third column shows the adjusted R-squared. The fourth column shows the F-statistic. The fifth column shows the number of observations. The sixth column shows the adjusted R-squared. The seventh column shows the F-statistic. The eighth column shows the number of observations. The ninth column shows the adjusted R-squared. The tenth column shows the F-statistic. The eleventh column shows the number of observations. The twelfth column shows the adjusted R-squared. The thirteenth column shows the F-statistic. The fourteenth column shows the number of observations. The fifteenth column shows the adjusted R-squared. The sixteenth column shows the F-statistic. The seventeenth column shows the number of observations. The eighteenth column shows the adjusted R-squared. The nineteenth column shows the F-statistic. The twentieth column shows the number of observations. The twenty-first column shows the adjusted R-squared. The twenty-second column shows the F-statistic. The twenty-third column shows the number of observations. The twenty-fourth column shows the adjusted R-squared. The twenty-fifth column shows the F-statistic. The twenty-sixth column shows the number of observations. The twenty-seventh column shows the adjusted R-squared. The twenty-eighth column shows the F-statistic. The twenty-ninth column shows the number of observations. The thirtieth column shows the adjusted R-squared. The thirty-first column shows the F-statistic. The thirty-second column shows the number of observations. The thirty-third column shows the adjusted R-squared. The thirty-fourth column shows the F-statistic. The thirty-fifth column shows the number of observations. The thirty-sixth column shows the adjusted R-squared. The thirty-seventh column shows the F-statistic. The thirty-eighth column shows the number of observations. The thirty-ninth column shows the adjusted R-squared. The fortieth column shows the F-statistic. The forty-first column shows the number of observations. The forty-second column shows the adjusted R-squared. The forty-third column shows the F-statistic. The forty-fourth column shows the number of observations. The forty-fifth column shows the adjusted R-squared. The forty-sixth column shows the F-statistic. The forty-seventh column shows the number of observations. The forty-eighth column shows the adjusted R-squared. The forty-ninth column shows the F-statistic. The fiftieth column shows the number of observations. The fifty-first column shows the adjusted R-squared. The fifty-second column shows the F-statistic. The fifty-third column shows the number of observations. The fifty-fourth column shows the adjusted R-squared. The fifty-fifth column shows the F-statistic. The fifty-sixth column shows the number of observations. The fifty-seventh column shows the adjusted R-squared. The fifty-eighth column shows the F-statistic. The fifty-ninth column shows the number of observations. The sixtieth column shows the adjusted R-squared. The sixty-first column shows the F-statistic. The sixty-second column shows the number of observations. The sixty-third column shows the adjusted R-squared. The sixty-fourth column shows the F-statistic. The sixty-fifth column shows the number of observations. The sixty-sixth column shows the adjusted R-squared. The sixty-seventh column shows the F-statistic. The sixty-eighth column shows the number of observations. The sixty-ninth column shows the adjusted R-squared. The seventieth column shows the F-statistic. The seventy-first column shows the number of observations. The seventy-second column shows the adjusted R-squared. The seventy-third column shows the F-statistic. The seventy-fourth column shows the number of observations. The seventy-fifth column shows the adjusted R-squared. The seventy-sixth column shows the F-statistic. The seventy-seventh column shows the number of observations. The seventy-eighth column shows the adjusted R-squared. The seventy-ninth column shows the F-statistic. The eightieth column shows the number of observations. The eighty-first column shows the adjusted R-squared. The eighty-second column shows the F-statistic. The eighty-third column shows the number of observations. The eighty-fourth column shows the adjusted R-squared. The eighty-fifth column shows the F-statistic. The eighty-sixth column shows the number of observations. The eighty-seventh column shows the adjusted R-squared. The eighty-eighth column shows the F-statistic. The eighty-ninth column shows the number of observations. The ninetieth column shows the adjusted R-squared. The ninety-first column shows the F-statistic. The ninety-second column shows the number of observations. The ninety-third column shows the adjusted R-squared. The ninety-fourth column shows the F-statistic. The ninety-fifth column shows the number of observations. The ninety-sixth column shows the adjusted R-squared. The ninety-seventh column shows the F-statistic. The ninety-eighth column shows the number of observations. The ninety-ninth column shows the adjusted R-squared. The one-hundredth column shows the F-statistic.

Table 26: Summary statistics for Stambaugh and Yuan four-factor model and earnings forecast errors

	11	12	13	14	15	21	22	23	24	25	31	32	33	34	35	41	42	43	44	45	51	52	53	54	55	
(Intercept)	-.08 (.04)	.00 (.04)	.05* (.02)	.05 (.02)	.10* (.04)	-.02 (.02)	.02 (.03)	.02 (.03)	-.02 (.05)	.02 (.04)	.01 (.06)	.00 (.02)	.00 (.03)	.03 (.02)	.01 (.02)	.05* (.02)	.01 (.02)	.01 (.02)	.05 (.03)	.05 (.04)	.01 (.02)	-.02 (.02)	.01 (.01)	.01 (.01)	-.02 (.04)	.04 (.04)
MKT-RF	1.23*** (.11)	1.04*** (.06)	1.06*** (.09)	1.13*** (.08)	1.13*** (.08)	1.12*** (.08)	1.02*** (.09)	1.02*** (.14)	1.00*** (.08)	1.01*** (.15)	1.06*** (.09)	1.13*** (.07)	1.01*** (.08)	1.01*** (.08)	1.01*** (.07)	.90*** (.08)	.95*** (.07)	.90*** (.06)	.95*** (.06)	.89*** (.10)	1.06*** (.06)	1.03*** (.08)	1.03*** (.05)	.86*** (.05)	.94*** (.08)	.79*** (.12)
SMBm	1.73*** (.20)	1.56*** (.18)	1.73*** (.16)	1.68*** (.12)	1.45*** (.11)	1.09*** (.15)	1.01*** (.16)	1.37*** (.21)	.76*** (.17)	1.22*** (.16)	.94*** (.18)	.96*** (.11)	.84*** (.12)	.75*** (.14)	.85*** (.10)	.71*** (.13)	.54*** (.09)	.76*** (.13)	.59*** (.14)	.63*** (.15)	-.24 (.13)	-.27** (.08)	-.12 (.08)	-.12 (.08)	-.13 (.17)	-.12 (.30)
MGM	-.56* (.23)	-.36 (.18)	-.12 (.17)	.17 (.10)	.23 (.13)	-.35** (.11)	.15 (.13)	.08 (.11)	.43* (.17)	.40* (.16)	-.33 (.17)	.02 (.06)	.33** (.12)	.33** (.12)	.33** (.12)	-.34** (.14)	.11 (.08)	.11 (.08)	.20 (.10)	.42 (.15)	-.42 (.21)	.24* (.10)	.14 (.12)	.14 (.12)	.52** (.27)	.22 (.19)
PERF	-.03 (.06)	.06 (.06)	.11 (.08)	.13* (.06)	-.06 (.06)	.13* (.05)	.03 (.04)	.10 (.05)	.06 (.06)	-.07 (.05)	.17* (.06)	.10 (.06)	-.01 (.05)	.09 (.05)	.09 (.05)	.08 (.03)	.08 (.05)	.06 (.04)	.12 (.07)	.12 (.09)	-.07 (.09)	.13 (.06)	.08 (.07)	.08 (.05)	.20** (.06)	.10 (.18)
EFE	-.84 (1.31)	.59 (2.17)	5.49** (1.79)	6.36*** (1.59)	9.76*** (2.25)	1.18 (.79)	4.70** (1.28)	5.72** (1.99)	3.88 (2.84)	9.65*** (2.42)	2.70* (1.11)	4.02*** (.71)	6.55*** (1.41)	10.26*** (1.52)	10.87*** (1.23)	4.97*** (1.27)	5.50** (1.61)	7.64*** (1.55)	6.88*** (1.52)	6.07*** (1.11)	-2.29 (2.31)	1.09 (1.30)	3.44* (1.26)	10.18*** (2.53)	10.02 (9.83)	10.02 (9.83)
R ²	.87	.84	.88	.89	.88	.86	.89	.90	.80	.74	.89	.93	.85	.81	.80	.89	.89	.87	.76	.67	.89	.89	.88	.88	.77	.47
Adj. R ²	.84	.81	.86	.87	.85	.84	.87	.88	.76	.70	.87	.92	.82	.78	.77	.87	.87	.85	.72	.61	.87	.87	.86	.86	.73	.37
Num. obs.	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34
F statistic	36.52	29.31	40.72	47.10	39.25	35.28	47.02	47.88	22.32	16.34	46.36	76.25	31.92	24.22	22.82	45.24	45.47	39.04	18.15	11.32	43.89	43.34	43.05	18.99	4.95	

The table tests the ability of the Stambaugh and Yuan four-factor model including earnings forecast errors to explain annual excess returns on 25 portfolios formed on size and book-to-market for the 31 portfolio formation years from 1982-2015. The value-weighted excess portfolio returns are calculated from July of year t to June of year t+1. The second number represents the book-to-market portfolio, x1 is the low book-to-market (Growth) portfolio and x5 is the high low book-to-market (Value) portfolio. Thus portfolio 11 is the Small-Growth portfolio and portfolio 55 is the Large-Value portfolio. The Stambaugh and Yuan four-factor model is comprised of the market excess return MKT-RF, the size factor of Stambaugh, SMBm, the mispricing factor related to variables that a firm's management can rather affect directly, MGM, and the performance-related mispricing factor, PERF. Value-weighted portfolio earnings forecast errors in the sort for June of year t are defined as firms' actual trailing 12 month earnings per share measured in June t+1 minus consensus 12 month expected earnings per share measured in June t, scaled by total assets per share in year t. Earnings forecast errors are trimmed every year at the 1 per cent and 99 per cent levels. Test-statistics are calculated using Newey and West (1987) standard errors with four lags, which are shown in parentheses. Coefficients with * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B R Session Info

```
devtools::session_info()
```

```
## - Session info -----  
## setting value  
## version R version 4.0.2 (2020-06-22)  
## os Windows 10 x64  
## system x86_64, mingw32  
## ui RTerm  
## language (EN)  
## collate German_Germany.1252  
## ctype German_Germany.1252  
## tz Europe/Berlin  
## date 2022-03-15  
##  
## - Packages -----  
## ! package * version date lib source  
## abind 1.4-5 2016-07-21 [1] CRAN (R 4.0.0)  
## assertthat 0.2.1 2019-03-21 [1] CRAN (R 4.0.0)  
## backports 1.1.7 2020-05-13 [1] CRAN (R 4.0.0)  
## bayestestR 0.7.2 2020-07-20 [1] CRAN (R 4.0.2)  
## bdsmatrix 1.3-4 2020-01-13 [1] CRAN (R 4.0.0)  
## bibtex 0.4.2.2 2020-01-02 [1] CRAN (R 4.0.0)  
## blob 1.2.1 2020-01-20 [1] CRAN (R 4.0.2)  
## bookdown * 0.20 2020-06-23 [1] CRAN (R 4.0.2)  
## boot 1.3-25 2020-04-26 [2] CRAN (R 4.0.2)
```

##	broom	0.7.0	2020-07-09	[1]	CRAN	(R 4.0.2)
##	broom.mixed	* 0.2.6	2020-05-17	[1]	CRAN	(R 4.0.0)
##	cachem	1.0.1	2021-01-21	[1]	CRAN	(R 4.0.3)
##	CADfTest	* 0.3-3	2017-06-02	[1]	CRAN	(R 4.0.0)
##	callr	3.5.1	2020-10-13	[1]	CRAN	(R 4.0.3)
##	car	3.0-8	2020-05-21	[1]	CRAN	(R 4.0.2)
##	carData	3.0-4	2020-05-22	[1]	CRAN	(R 4.0.0)
##	cellranger	1.1.0	2016-07-27	[1]	CRAN	(R 4.0.0)
##	checkmate	2.0.0	2020-02-06	[1]	CRAN	(R 4.0.2)
##	cli	2.0.2	2020-02-28	[1]	CRAN	(R 4.0.0)
##	coda	0.19-3	2019-07-05	[1]	CRAN	(R 4.0.0)
##	colorspace	1.4-1	2019-03-18	[1]	CRAN	(R 4.0.0)
##	cowplot	* 1.0.0	2019-07-11	[1]	CRAN	(R 4.0.0)
##	crayon	1.3.4	2017-09-16	[1]	CRAN	(R 4.0.0)
##	curl	4.3	2019-12-02	[1]	CRAN	(R 4.0.0)
##	data.table	* 1.13.0	2020-07-24	[1]	CRAN	(R 4.0.2)
##	DBI	1.1.0	2019-12-15	[1]	CRAN	(R 4.0.0)
##	dbplyr	1.4.4	2020-05-27	[1]	CRAN	(R 4.0.2)
##	desc	1.2.0	2018-05-01	[1]	CRAN	(R 4.0.0)
##	devtools	* 2.3.2	2020-09-18	[1]	CRAN	(R 4.0.3)
##	digest	0.6.25	2020-02-23	[1]	CRAN	(R 4.0.0)
##	dplyr	* 1.0.1	2020-07-31	[1]	CRAN	(R 4.0.2)
##	dynlm	* 0.3-6	2019-01-06	[1]	CRAN	(R 4.0.0)
##	effectsize	0.3.2	2020-07-27	[1]	CRAN	(R 4.0.2)
##	ellipsis	0.3.1	2020-05-15	[1]	CRAN	(R 4.0.0)
##	emmeans	1.4.8	2020-06-26	[1]	CRAN	(R 4.0.2)

##	estimability	1.3	2018-02-11	[1]	CRAN	(R 4.0.0)
##	estimatr	* 0.22.0	2020-03-19	[1]	CRAN	(R 4.0.0)
##	evaluate	0.14	2019-05-28	[1]	CRAN	(R 4.0.0)
##	fansi	0.4.1	2020-01-08	[1]	CRAN	(R 4.0.0)
##	farver	2.0.3	2020-01-16	[1]	CRAN	(R 4.0.0)
##	fastmap	1.1.0	2021-01-25	[1]	CRAN	(R 4.0.3)
##	fBasics	* 3042.89.1	2020-03-07	[1]	CRAN	(R 4.0.0)
##	forcats	* 0.5.0	2020-03-01	[1]	CRAN	(R 4.0.0)
##	forecast	* 8.12	2020-03-31	[1]	CRAN	(R 4.0.2)
##	foreign	0.8-80	2020-05-24	[2]	CRAN	(R 4.0.2)
##	Formula	1.2-3	2018-05-03	[1]	CRAN	(R 4.0.0)
##	fracdiff	1.5-1	2020-01-24	[1]	CRAN	(R 4.0.2)
##	fs	1.5.0	2020-07-31	[1]	CRAN	(R 4.0.2)
##	fUnitRoots	* 3042.79	2017-11-16	[1]	CRAN	(R 4.0.0)
##	gbRd	0.4-11	2012-10-01	[1]	CRAN	(R 4.0.0)
##	generics	0.0.2	2018-11-29	[1]	CRAN	(R 4.0.0)
##	ggeffects	0.15.1	2020-07-27	[1]	CRAN	(R 4.0.2)
##	ggplot2	* 3.3.2	2020-06-19	[1]	CRAN	(R 4.0.2)
##	ggpubr	* 0.4.0	2020-06-27	[1]	CRAN	(R 4.0.2)
##	ggsignif	0.6.0	2019-08-08	[1]	CRAN	(R 4.0.0)
##	ggstance	0.3.4	2020-04-02	[1]	CRAN	(R 4.0.0)
##	glue	1.4.1	2020-05-13	[1]	CRAN	(R 4.0.0)
##	gridExtra	* 2.3	2017-09-09	[1]	CRAN	(R 4.0.0)
##	gtable	0.3.0	2019-03-25	[1]	CRAN	(R 4.0.0)
##	gtools	* 3.8.2	2020-03-31	[1]	CRAN	(R 4.0.0)
##	haven	2.3.1	2020-06-01	[1]	CRAN	(R 4.0.2)

##	highr	0.8	2019-03-20	[1]	CRAN (R 4.0.0)
##	hms	0.5.3	2020-01-08	[1]	CRAN (R 4.0.0)
##	htmltools	0.5.0	2020-06-16	[1]	CRAN (R 4.0.2)
##	httr	1.4.2	2020-07-20	[1]	CRAN (R 4.0.2)
##	insight	0.9.0	2020-07-20	[1]	CRAN (R 4.0.2)
##	jsonlite	1.7.2	2020-12-09	[1]	CRAN (R 4.0.3)
##	jtools	* 2.1.0	2020-06-23	[1]	CRAN (R 4.0.2)
##	kableExtra	* 1.1.0	2019-03-16	[1]	CRAN (R 4.0.0)
##	knitr	* 1.29	2020-06-23	[1]	CRAN (R 4.0.2)
##	labeling	0.3	2014-08-23	[1]	CRAN (R 4.0.0)
##	lattice	0.20-41	2020-04-02	[2]	CRAN (R 4.0.2)
##	lfe	* 2.8-5.1	2020-07-08	[1]	CRAN (R 4.0.2)
##	lifecycle	0.2.0	2020-03-06	[1]	CRAN (R 4.0.0)
##	lme4	1.1-23	2020-04-07	[1]	CRAN (R 4.0.0)
##	lmtest	* 0.9-37	2019-04-30	[1]	CRAN (R 4.0.0)
##	lubridate	1.7.9	2020-06-08	[1]	CRAN (R 4.0.2)
##	magrittr	1.5	2014-11-22	[1]	CRAN (R 4.0.0)
##	MASS	7.3-51.6	2020-04-26	[2]	CRAN (R 4.0.2)
##	Matrix	* 1.2-18	2019-11-27	[2]	CRAN (R 4.0.2)
##	maxLik	1.4-0	2020-07-31	[1]	CRAN (R 4.0.2)
##	memoise	2.0.0	2021-01-26	[1]	CRAN (R 4.0.3)
##	minqa	1.2.4	2014-10-09	[1]	CRAN (R 4.0.0)
##	miscTools	0.6-26	2019-12-08	[1]	CRAN (R 4.0.0)
##	modelr	0.1.8	2020-05-19	[1]	CRAN (R 4.0.0)
##	munsell	0.5.0	2018-06-12	[1]	CRAN (R 4.0.0)
##	mvtnorm	1.1-1	2020-06-09	[1]	CRAN (R 4.0.0)

##	nlme	3.1-148	2020-05-24	[2]	CRAN	(R 4.0.2)
##	nloptr	1.2.2.2	2020-07-02	[1]	CRAN	(R 4.0.2)
##	nnet	7.3-14	2020-04-26	[2]	CRAN	(R 4.0.2)
##	openxlsx	* 4.1.5	2020-05-06	[1]	CRAN	(R 4.0.0)
##	pander	0.6.3	2018-11-06	[1]	CRAN	(R 4.0.0)
##	parameters	0.8.2	2020-07-24	[1]	CRAN	(R 4.0.2)
##	performance	0.4.8	2020-07-27	[1]	CRAN	(R 4.0.2)
##	PerformanceAnalytics	* 2.0.4	2020-02-06	[1]	CRAN	(R 4.0.2)
##	pillar	1.4.6	2020-07-10	[1]	CRAN	(R 4.0.2)
##	pkgbuild	1.1.0	2020-07-13	[1]	CRAN	(R 4.0.2)
##	pkgconfig	2.0.3	2019-09-22	[1]	CRAN	(R 4.0.0)
##	pkgload	1.1.0	2020-05-29	[1]	CRAN	(R 4.0.2)
##	plm	* 2.2-3	2020-02-28	[1]	CRAN	(R 4.0.0)
##	plyr	1.8.6	2020-03-03	[1]	CRAN	(R 4.0.0)
##	prettyunits	1.1.1	2020-01-24	[1]	CRAN	(R 4.0.0)
##	processx	3.4.5	2020-11-30	[1]	CRAN	(R 4.0.3)
##	ps	1.3.3	2020-05-08	[1]	CRAN	(R 4.0.0)
##	purrr	* 0.3.4	2020-04-17	[1]	CRAN	(R 4.0.0)
##	quadprog	1.5-8	2019-11-20	[1]	CRAN	(R 4.0.0)
##	quantmod	0.4.17	2020-03-31	[1]	CRAN	(R 4.0.0)
##	R6	2.4.1	2019-11-12	[1]	CRAN	(R 4.0.0)
##	Rcpp	1.0.5	2020-07-06	[1]	CRAN	(R 4.0.2)
##	Rdpack	1.0.0	2020-07-01	[1]	CRAN	(R 4.0.2)
##	readr	* 1.3.1	2018-12-21	[1]	CRAN	(R 4.0.0)
##	readxl	1.3.1	2019-03-13	[1]	CRAN	(R 4.0.0)
##	remotes	2.2.0	2020-07-21	[1]	CRAN	(R 4.0.2)

##	reprex	0.3.0	2019-05-16	[1]	CRAN	(R 4.0.0)
##	reshape2	1.4.4	2020-04-09	[1]	CRAN	(R 4.0.0)
##	rio	0.5.16	2018-11-26	[1]	CRAN	(R 4.0.0)
##	rlang	0.4.7	2020-07-09	[1]	CRAN	(R 4.0.2)
##	rmarkdown	2.3	2020-06-18	[1]	CRAN	(R 4.0.2)
##	rollRegres	* 0.1.3	2019-11-25	[1]	CRAN	(R 4.0.2)
##	rprojroot	1.3-2	2018-01-03	[1]	CRAN	(R 4.0.0)
##	rstatix	0.6.0	2020-06-18	[1]	CRAN	(R 4.0.2)
##	rstudioapi	0.11	2020-02-07	[1]	CRAN	(R 4.0.0)
##	rvest	0.3.6	2020-07-25	[1]	CRAN	(R 4.0.2)
##	sandwich	* 2.5-1	2019-04-06	[1]	CRAN	(R 4.0.0)
##	scales	1.1.1	2020-05-11	[1]	CRAN	(R 4.0.0)
##	sessioninfo	1.1.1	2018-11-05	[1]	CRAN	(R 4.0.3)
##	sjlabelled	1.1.6	2020-06-25	[1]	CRAN	(R 4.0.2)
##	sjmisc	2.8.5	2020-05-28	[1]	CRAN	(R 4.0.2)
##	sjPlot	* 2.8.4	2020-05-24	[1]	CRAN	(R 4.0.2)
##	sjstats	0.18.0	2020-05-06	[1]	CRAN	(R 4.0.0)
##	spatial	7.3-12	2020-04-26	[2]	CRAN	(R 4.0.2)
##	stargazer	* 5.2.2	2018-05-30	[1]	CRAN	(R 4.0.0)
##	statmod	1.4.34	2020-02-17	[1]	CRAN	(R 4.0.0)
##	stringi	1.4.6	2020-02-17	[1]	CRAN	(R 4.0.0)
##	stringr	* 1.4.0	2019-02-10	[1]	CRAN	(R 4.0.0)
##	testthat	2.3.2	2020-03-02	[1]	CRAN	(R 4.0.0)
##	texreg	* 1.37.5	2020-06-18	[1]	CRAN	(R 4.0.2)
##	tibble	* 3.0.3	2020-07-10	[1]	CRAN	(R 4.0.2)
##	tidyr	* 1.1.1	2020-07-31	[1]	CRAN	(R 4.0.2)

```

## tidyselect          1.1.0      2020-05-11 [1] CRAN (R 4.0.0)
## tidyverse          * 1.3.0      2019-11-21 [1] CRAN (R 4.0.0)
## timeDate           * 3043.102  2018-02-21 [1] CRAN (R 4.0.0)
## timeSeries         * 3062.100  2020-01-24 [1] CRAN (R 4.0.0)
## D TMB              1.7.18     2020-07-27 [1] CRAN (R 4.0.2)
## tseries            * 0.10-47   2019-06-05 [1] CRAN (R 4.0.0)
## TTR                * 0.23-6    2019-12-15 [1] CRAN (R 4.0.0)
## urca               * 1.3-0     2016-09-06 [1] CRAN (R 4.0.0)
## usethis            * 2.0.0     2020-12-10 [1] CRAN (R 4.0.3)
## vctrs              0.3.2      2020-07-15 [1] CRAN (R 4.0.2)
## viridisLite        0.3.0      2018-02-01 [1] CRAN (R 4.0.0)
## webshot            0.5.2      2019-11-22 [1] CRAN (R 4.0.0)
## withr              2.4.1      2021-01-26 [1] CRAN (R 4.0.3)
## xfun               0.16       2020-07-24 [1] CRAN (R 4.0.2)
## xml2               1.3.2      2020-04-23 [1] CRAN (R 4.0.0)
## xtable             1.8-4      2019-04-21 [1] CRAN (R 4.0.0)
## xts                * 0.12-0    2020-01-19 [1] CRAN (R 4.0.0)
## yaml               2.2.1      2020-02-01 [1] CRAN (R 4.0.0)
## zip                2.1.1      2020-08-27 [1] CRAN (R 4.0.3)
## zoo                * 1.8-8     2020-05-02 [1] CRAN (R 4.0.0)
##
## [1] C:/Users/User/Documents/R/win-library/4.0
## [2] C:/Program Files/R/R-4.0.2/library
##
## D -- DLL MD5 mismatch, broken installation.

```

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