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Essays on Empirical Asset Pricing and Behavioral Finance

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Chapter 1
Introduction

In its simplest form, a factor is a persistent and robust driver of expected returns which – if appropriately applied – has the potential to construct systematical investment strategies with an attractive risk/return profile. Whilst the underlying research on the cross-section of stock returns dates back several decades to the seminal studies of Markowitz (1952), Sharpe (1964), and Lintner (1965), the widespread practical application of academical research only recently gained traction through the rapid growth of so-called smart beta ETFs – systematic investment strategies embedded in passive investment vehicles. Despite outstanding results on paper, the live performance of respective products rather disappoints raising questions about the validity and robustness of documented return anomalies (Blitz, 2018; Blitz and Vidojevic, 2019). Indeed, the dismissal performance comes at no surprise when one considers carefully recent critics amongst academic researchers. In fact, numerous studies conduct comprehensive out-of-sample test of previously found return anomalies and come to the conclusion that a large fraction of claimed anomalies are actually the result of data-mining and data-selection (see Harvey et al. (2016), Green et al. (2017), or Hou et al. (2020) among others).

Another possibility for the underperformance out-of-sample is that respective return premia exist due to behavioral biaseses and get arbitraged away over time. In fact, McLean and Pontiff (2016) analyze 97 anomalies and come to the conclusion that previously documented return premia decrease on average by 58% after the respective academical paper was published. The post-publication decline is even larger the higher the in-sample return effect is. Additionally, they show that post-publication returns are higher for stocks with a low liquidity and high idiosyncratic risk. Ultimately, this suggests that a large fraction of documented return premia are the result of mispricing which, if possible, gets arbitraged away over time. Additionally, this implies that market participants learn about respective mispricing from academic publications.

To take these developments into account, the first part of this thesis focuses on two of the most prominent return effects, namely the momentum anomaly and the value anomaly with the aim to develop a better understanding about the existence of the respective premia. Further on, the second part of this thesis focuses on two major aspects of behavioral finance – investor sentiment and continuing overreaction. Given the fact that a large fraction of market anomalies is attributable to mispricing, more sophisticated measures to gauge investor sentiment provide a wide range of possible applications not just for academics but practitioners as well. As most financial research studies focus on US markets (Karolyi, 2016), this thesis concentrates on developed capital markets outside the US, which resemble a comprehensive out-of-sample test setting. In the remainder of the introduction, I provide an overview of the four studies regarding the underlying motivation, the contents, and the contributions.

Separating momentum from reversal in inaternational stock markets

Introduced in 1993 by Jegadeesh and Titman, the momentum anomaly is one of the most examined yet robust return effects in finance history. Based on past twelve-month returns, they show that previous winners continue to outperform previous losers. Yet, an explanation for the existence of the anomaly is still missing up to this date. One drawback of a standard momentum strategy is the reversal effect. Specifically, the positive premium reverses one year after portfolio formation and becomes significantly negative. Recent evidence provided by Conrad and Yavuz (2017), however, suggests that it is possible to separate between stocks that experience momentum and stocks that suffer from reversal ex-ante using firm fundamentals.

Therefore, our analysis focuses on the effectiveness of firm fundamentals to differentiate between stocks that experience momentum and stocks that suffer from reversal in international out-of-sample tests. In detail, our analysis framework is based on Fama-MacBeth (1973) cross-sectional regressions, which allows us to simultaneously control for multiple return effects. Furthermore, taking various evidence of macroeconomic effects on momentum strategies into account, we investigate the pervasiveness of our results within different market states. Finally, we employ a test setting to investigate cross-sectional mispricing across firms using a firm's external financing behavior (Bradshaw et al. 2006) to proxy for systematic mispricing.

Our results confirm previous evidence suggesting that investors are able to differentiate between stocks that experience momentum and stocks that solely suffer from reversal ex-ante. In particular, a strategy that buys small value winners and sells short large growth losers significantly outperforms a standard momentum strategy and does not show a return reversal in the second and third year after portfolio formation. Contrary to this, a strategy that buys large growth winners and sells short small value losers does not produce a return premium at all and exhibits a significantly negative return premium in the second and third year after portfolio formation. Additionally, we contribute to the existing literature by providing evidence that the return difference of two momentum strategies is due to systematic exploitation of cross-sectional mispricing among stocks.

Overnight Returns: An International Sentiment Measure

The role of investor sentiment in the context of return anomalies is a topic of substantial interest within asset pricing research. However, most proxies focus on market-wide sentiment measures and the US equity market due to data availability issues. The well-known sentiment index of Baker and Wurgler (2006) is just one example. Besides data availability issues, market-wide sentiment measures have the shortcoming that they are invariant in the cross-section and therefore not suitable to study the effects of investor sentiment at the firm-level.

The second research study in Chapter 3 examines the suitability of overnight returns as a proxy for investor sentiment proposed by Aboody et al. (2018) in an international setting. Previous evidence suggests that retail investors are mostly affected by sentiment and tend to act as a herd accordingly. Furthermore, retails investors tend to place their orders overnight, which are ultimately executed at the open of the following trading day. Contrary to that, institutional investors mostly trade during the opening hours of an exchange due to lower trading costs and liquidity concerns. Based on those findings, overnight returns are heavily influenced by the irrational trading behavior of sentiment-driven retail investors.

Our analysis provides strong support in favor of the hypothesis that overnight returns function as a proxy for investor sentiment at the individual firm-level. First, overnight returns are significantly persistent in the short-run even after controlling for a large set of well-known return effects. Second, the persistence is even stronger for firms which can be characterized as harder to value. Third, stocks with high (low) short-term overnight returns experience a negative (positive) reversal in close-to-close returns long-term. Finally, using the momentum anomaly as a test-setting itself, we provide evidence that overnight returns as a sentiment measure exhibit predictive power while controlling for market-wide sentiment using the index proposed by Baker and Wurgler (2006).

Continuing Overreaction: European Evidence

The momentum anomaly is one of the most examined return anomalies in finance. Despite being already introduced in 1993 by Jegadeesh and Titman, there is no uniform explanation for the existence of the return premium up to this date. One central model which is able to explain not just momentum but also the documented reversal effect after 12 months is proposed by Daniel et al. (1998). Specifically, investors tend to overestimate their own abilities which lead them to overvalue private information while underreacting to public information. As a consequence, the confidence of investors rises and leads to biased self-attribution if a public signal confirms their private information and buy (sell) decision. Such a behavior would explain why past returns are informative about future returns and ultimately why momentum in the short-term and reversal in the long-term arises.

Based upon this insight, Byun et al. (2016) develop a measure to proxy for overreaction based on past returns and trading volumes. Indeed, if momentum is caused by continuing overreaction, a more direct measure should be more informative about expected returns and should be able to explain the momentum anomaly. Besides the application in the context of the momentum anomaly, such a measure could be used to explain and better understand a wide range of behavioral motivated return effects. We provide evidence that the proposed continuing overreaction measure is informative about the cross-section of expected returns even after controlling for momentum. In addition and contrary to a standard momentum strategy, the premium associated with continuing overreaction does not suffer from a reversal effect. The superior performance over momentum returns holds up in the presence of other return controls and within different business conditions, which suggests that the measure indeed captures continuing overreaction.

Dissecting Value-Growth Strategies Conditioned on Expectation Errors

The value premium describes the outperformance of firms with high book-to-market ratios over firms with low book-to-market ratios. While originally being tied to a risk-based explanation by Fama and French (1993), the explanation that the premium is due to behavioral biases gets more and more traction in recent years. Piotroski and So (2012) provide evidence in favor of a mispricing-based explanation using a proxy for a firm's underlying fundamental strength, namely the FSCORE. In detail, they show that the value premium only exists for firms where expectations implied by a firm's book-to-market ratio are incongruent with a firm's fundamental strength. Following their publication, numerous research studies demonstrated the robustness and usefulness of the FSCORE to explain the value premium, other fundamental motivated premia, and even the momentum premium (see for example Walkshäusl, 2017; Tikkanen and Äijo, 2018; Ahmed and Shafdar, 2018).

The fourth study in Chapter 5 examines the influence of FSCORE on the value premium using a present value model originally proposed by Cohen et al. (2003). According to their results, the return spread between value and growth firms is not due to differences in expected returns but rather due to differences in expected profitability. As the FSCORE strongly correlates with a firm‘s profitability, the evidence of Cohen et al. (2003) indirectly challenges the mispricing-related explanation of Piotroski and So (2012), which implies differences in expected returns.

First of all, we show that the existence of the value premium strongly depends on a firm's fundamental strength proxied by the FSCORE, which is in line with previous evidence. In detail, this means that the high returns of value firms are due to value firms with strong fundamentals whereas the low returns of growth firms are due to growth firms with weak fundamentals. Second, considering all value and growth firms, we confirm the results of Cohen et al. (2003) that differences in book-to-market ratios are mostly due to variations in expected cashflows and not due to differences in expected returns. However, taking a firm's FSCORE into account, the expected return component significantly varies between the different value-growth samples. This result strongly supports the market expectation errors hypothesis proposed by Piotroski and So (2012) and eliminates the possibility that the return differences induced by the FSCORE are due to differences in expected profitability.

The first two research studies presented below are published in academic journals, while the last two papers are under review at the date of the submission of this thesis. Minor formal differences in the presentation of the four papers may be present, which is due to differences regarding style requirements employed by the respective journal.

Chapter 2

Separating momentum from reversal in international stock markets

This research paper is joint work with Christian Walkshäusl and Florian Weißofner. The paper was published as: Christian Walkshäusl, Florian Weißofner, and Ulrich Wessels (2019), Separating momentum from reversal in international stock markets, *Journal of Asset Management* 20, 111-123. The journal ranking is B according to the VHB JOURQUAL 3 (2015) journal quality list.

Abstract Taking into account expected return characteristics like firm size and book-to-market in the selection of winners and losers helps to ex ante separate stocks with momentum from those that exhibit reversal in international equity markets. A strategy that buys small value winners and sells large growth losers generates significantly larger momentum profits than a standard momentum strategy, is robust to common return controls, and does not suffer from return reversals for holding periods up to three years. The superior performance of the strategy is attributable to a rather systematic exploitation of cross-sectional mispricing among momentum stocks.

Keywords Momentum, Reversal, Return predictability, Mispricing, International markets

2.1 Introduction

Over the last three decades, the momentum effect has become one of the most examined return patterns in finance. In their seminal work, Jegadeesh and Titman (1993) demonstrate that a strategy that buys past winners and sells past losers produces large abnormal returns for holding periods up to one year. Since then, the momentum effect has been documented in international equity markets, within industries, and across different asset classes (Rouwenhorst, 1998; Moskowitz and Grinblatt, 1999; Asness *et al*, 2013). However, over longer holding periods, momentum portfolios, in general, suffer from a return reversal pattern, i.e., the abnormal returns earned over the first year after portfolio formation reverse or even turn negative in subsequent years (Jegadeesh and Titman, 2001; Blackburn and Cakici, 2017).

Despite the enormous body of literature on the momentum effect, explanations for the return behavior of momentum stocks remain an ongoing debate. Daniel *et al* (1998) were among the first to present a behavioral model based on investors' overconfidence that explains the short-term return continuation and long-term return reversal patterns of typical momentum strategies. Conrad and Kaul (1998) suggest a risk-based explanation that is, however, contradicted by Jegadeesh and Titman (2002) who argue that momentum portfolios should not suffer from return reversals if the risk-based interpretation is correct.[1]

Recently, Conrad and Yavuz (2017) take up again this debate by arguing that stocks with momentum can be separated from those that exhibit reversal when risk-based expected return characteristics like firm size and book-to-market are taken into account in the selection of winners and losers. Assuming that these firm characteristics are responsible for differences in expected returns (Fama and French, 1992), they construct two distinct momentum strategies that differ in their underlying risk characteristics. The MAX momentum strategy takes a long position in high-risk winners, i.e., small value winners, and a short position in low-risk losers, i.e., large growth losers. Analogously, the MIN momentum strategy goes long in low-risk winners (large growth winners) and short in high-risk losers (small value losers).

Studying the U.S. equity market, Conrad and Yavuz (2017) find that the MAX strategy does not only yield larger momentum profits than the standard momentum strategy in the short run, it also does not display significant return reversals for holding periods beyond one year. In

[1] See, Jegadeesh and Titman (2011) for an extended review of the literature.

contrast to that, the MIN strategy produces no significant momentum profits in the short run but suffers from substantial and significant return reversals in the long run. Thus, short-term return continuation and long-term return reversals are not necessarily linked. Taking into account expected return characteristics like firm size and book-to-market in the selection of winners and losers helps to *ex ante* separate stocks with momentum from those that exhibit reversal.

The approach of Conrad and Yavuz (2017) seems to be related to the style momentum of Chen and DeBondt (2004) who propose a strategy that goes long in firms with in-favor styles, e.g., being small value stocks, and short in firms with out-of-favor styles, e.g., being large growth stocks, based on the past price performance of these style characteristics. However, there exist clear differences. First, Chen and DeBondt (2004) document in their study that style momentum is distinct from pure price momentum by showing that both strategies possess unique information about subsequent stock returns that is not captured by the other strategy. Second, though the MAX and MIN strategies also take into account firm size and book-to-market in the selection of winners and losers, the focus of these strategies is on using these characteristics as risk measures for separating high-risk from low-risk momentum stocks. Consequently, the strategies' long and short legs are uniformly defined. In contrast, the long and short leg portfolios of style momentum strategies can potentially also consist of mid-cap blend-style stocks or non-dividend-paying stocks, which are not in the center of attention of the MAX and MIN strategies. Third and finally, while the motivation of Chen and DeBondt (2004) is the improvement of style rotation strategies with respect to firm size and value/growth, the MAX and MIN strategies are motivated by the idea that momentum can be separated from reversal for constructing enhanced momentum-based investment strategies.

In this paper, we contribute to the literature by studying the findings of Conrad and Yavuz (2017) outside the United States. As with any finding in empirical research, the decomposition of momentum and reversal could be the result of data snooping in the sense of Lo and MacKinlay (1990) and therefore be sample-specific. To address this concern, we independently examine in this study the novel MAX and MIN strategies in the broad cross-section of international firms drawn from 20 developed non-U.S. equity markets. Obtaining results similar to the previous U.S. evidence in Conrad and Yavuz (2017) would strengthen their findings and may lead to a better understanding of the momentum and reversal return patterns across equity markets.

From the previous U.S. evidence, we derive three hypotheses that we test out-of-sample in non-U.S. equity markets. The first hypothesis directly addresses whether international stock returns conform to the same pattern observed in the United States.

H1: *A strategy that buys small value winners and sells large growth losers, the MAX strategy, yields significantly larger benchmark-adjusted returns over holding periods up to one year than a strategy that buys large growth winners and sells small value losers, the MIN strategy.*

Showing that the short-term performance of the MAX strategy is superior to the MIN strategy is only the first part of the key results of Conrad and Yavuz (2017). Second and even more important may be the finding that considering expected return characteristics like firm size and book-to-market in the selection of winners and losers helps to *ex ante* separate momentum stocks that display return reversals from those that do not. Therefore, we further investigate the return behavior of the MAX and MIN strategies over longer holding periods up to three years and formulate our second hypothesis as follows.

H2: *Over holding periods beyond one year, the MAX strategy displays no return reversal, while the MIN strategy exhibits significant return reversal.*

The distinct return behavior of the MAX and MIN strategies may be attributable to the varying underlying risks associated with different levels of firm size and book-to-market, as argued by Conrad and Yavuz (2017). However, these well-known firm characteristics can also be interpreted as measures of mispricing (e.g., Lakonishok *et al*, 1994; Shleifer and Vishney, 1997; Hirshleifer and Jiang, 2010). Though Conrad and Yavuz (2017) reject that the level of market-wide mispricing as measured by market states and the investor sentiment is influential in the results observed, they do not rule out explanations based on cross-sectional mispricing. That is, the possibility that the different return behavior of the two strategies is the result of a rather systematic exploitation of existing mispricing among momentum stocks that is induced by taking into account mispricing-related measures like firm size and book-to-market in the stock selection procedure. Because mispricing at the individual firm level may add to our understanding of the varying return behavior of the MAX and MIN strategies, we formulate our third and final hypothesis as follows.

H3: *The strong performance of the MAX strategy and the weak performance of the MIN strategy are the outcome of cross-sectional mispricing.*

The remainder of the paper is organized as follows. The next section describes the data and variables used in this study. The subsequent sections test the outlined hypotheses and present the empirical results. The final section concludes the paper.

2.2 Data and summary statistics

The dataset used in this study consists of an international sample of firms from 20 developed non-U.S. equity markets. Our sample selection resembles the countries included in the well-known EAFE (Europe, Australia, and the Far East) stock market benchmark from MSCI which measures the foreign stock market performance outside of North America. We collect monthly total return data on common stocks from Datastream and firm-level accounting information from Worldscope. To ensure that accounting information is known before the returns are calculated, we match the latest accounting information for the fiscal year ending in the previous calendar year with stock returns from July of the current year to June of the subsequent year throughout the paper. All data are denominated in U.S. dollars. To ensure that tiny or illiquid stocks do not drive our results, we follow Ang *et al* (2009) and exclude very small firms by eliminating the 5% of firms with the lowest market equity in each country. In addition, as in Fama and French (1992), we also exclude firm-year observations with negative book equity and financial firms with Standard Industrial Classification (SIC) codes between 6000 and 6999. The sample period is from July 1990 to June 2017 (henceforth 1990-2017), and the sample comprises on average 7652 firms per month. Distributional statistics for the sample firms across countries are given in Panel A of Table 1.

Table 2.1 Summary statistics 1990-2017

Panel A: Sample countries

Country	Firms	Country	Firms
Australia	745	Japan	2631
Austria	56	Netherlands	109
Belgium	79	New Zealand	68
Denmark	97	Norway	114
Finland	85	Portugal	49
France	530	Singapore	311
Germany	523	Spain	98
Hong Kong	490	Sweden	233
Ireland	39	Switzerland	144
Italy	159	United Kingdom	1092

Panel B: Variables

Variable	Mean	25th	Median	75th
SZ	955	40	126	464
BM	0.96	0.40	0.72	1.21
MOM	0.05	-0.14	0.01	0.18
OP	0.74	0.25	0.52	0.92
INV	0.16	-0.04	0.05	0.18
XFIN	0.08	-0.04	-0.01	0.04

This table presents summary statistics for the countries included in the international (EAFE) sample and the variables used in this study. Panel A reports the average number of firms per month in each country over the sample period from July 1990 to June 2017. Panel B reports the mean, 25th percentile, median, and 75th percentile of the variables. Firm size (SZ) is market equity (stock price multiplied by the number of shares outstanding) as of June of each year in million U.S. dollars. Book-to-market (BM) is the ratio of book equity to market equity at the fiscal year-end. Momentum (MOM) is the cumulative prior six-month stock return, skipping the most recent month. Operating profitability (OP) is revenues minus cost of goods sold and interest expense, all divided by book equity. Investment (INV) is the annual change in total assets divided by total assets. External financing (XFIN) is the sum of net equity financing and net debt financing divided by lagged total assets. Net equity financing is the sale of common and preferred stock minus the purchase of common and preferred stock minus cash dividends paid. Net debt financing is the issuance of long-term debt minus the reduction in long-term debt.

The variables used in this study are defined as follows. A firm's size (SZ) is its market equity (stock price multiplied by the number of shares outstanding) measured as of June each year in million U.S. dollars. Book-to-market (BM) is the ratio of book equity to market equity at the fiscal year-end. Momentum (MOM) is the cumulative prior six-month stock return, skipping the most recent month (Jegadeesh and Titman, 1993). Following Fama and French (2015), operating profitability (OP) is revenues minus cost of goods sold and interest expense, all divided by book equity.[2] Investment (INV) is the annual change in total assets divided by lagged total assets. To proxy for systematic mispricing in the later analysis, we employ a financing-based misvaluation measure that is based on Bradshaw *et al*'s (2006) external financing (XFIN) variable. XFIN is the sum of net equity financing and net debt financing divided by lagged total assets. Net equity financing is the sale of common and preferred stock minus the purchase of common and preferred stock minus cash dividends paid. Net debt financing is the issuance of long-term debt minus the reduction in long-term debt.[3]

[2] We do not include selling, general and administrative expenses, as this item is not broadly available among international firms. The return predictability of operating profitability is, however, not affected by this adjustment.
[3] In line with Hirshleifer and Jiang (2010), we do not include the change in current debt, as it does not reflect market timing.

Panel B of Table 1 summarizes the distributional statistics of the variables over the 1990-2017 sample period. A typical firm in our international sample has a size of $955 million in terms of market equity, an average relative valuation based on book-to-market of 0.96, and a mean past six-month return of 5%.

2.3 Abnormal returns of MAX and MIN strategies

In this section, we test hypothesis H1 that the MAX strategy yields larger benchmark-adjusted returns than the MIN strategy. To do so, we examine the returns to winners and losers on the MAX and MIN strategies at the individual firm level using the Fama and MacBeth (1973) methodology and conduct differences-of-means tests on the average coefficient estimates from the regressions. For comparison purposes, we also include the standard momentum strategy in the analysis to gauge the strength of the MAX and MIN momentum premiums in relation to the unconditional momentum investing approach in international equity markets.

In particular, we estimate three different specification variants nested within the following firm-level cross-sectional regression, where the future twelve-month holding period return of firm i in month t is regressed on two binary indicator variables, denoted Long and Short, in conjunction with common controls that are all available before the month in which the return measurement begins:

$$\begin{aligned} r_{i,t} = a_{0,t} + a_{1,t}\mathrm{Long}_{i,t} + a_{2,t}\mathrm{Short}_{i,t} + a_{3,t}\ln(\mathrm{SZ}_{i,t}) + a_{4,t}\mathrm{BM}_{i,t} + a_{5,t}\mathrm{OP}_{i,t} \\ + a_{6,t}\mathrm{INV}_{i,t} + \text{Country Dummies}_{i,t} + e_{i,t}. \end{aligned} \tag{1}$$

We apply Newey and West (1987) adjusted t-statistics here and in all subsequent regressions to correct for the holding period overlap in the statistical inference (Jegadeesh and Titman, 1993). An indicator variable takes the value of one if the underlying condition holds for a firm and zero otherwise. For the standard momentum strategy, Long and Short are equal to one if the firm's past six-month return is in the top or bottom tercile of the MOM distribution, respectively. Thus, the long leg describes winners, while the short leg denotes losers. When studying the MAX and MIN strategies, the indicator variables also take into account the firm's size and book-to-market ratio as expected return characteristics in line with Conrad and Yavuz (2017). For the MAX strategy, Long is equal to one if the firm has a past-six month return in the top tercile of the MOM distribution and simultaneously a firm size in the bottom tercile of the SZ distribution and a book-to-market ratio in the top tercile of the BM distribution. Thus, classifying the firm as a small value winner. On the other hand, Short is equal to one if the firm has a past-six month return in the bottom tercile of the MOM distribution and simultaneously a firm size in the top tercile of the SZ distribution and a book-to-market ratio in the bottom tercile of the BM distribution. Thus, classifying the firm as a large growth loser. For the MIN strategy, the indicator variables are defined in an analogous manner using the tercile classifications based on SZ, BM, and MOM. In particular, Long is here equal to one if the firm is a large growth winner and Short is equal to one if the firm is a small value loser.[4]

Taking into account the most recent developments in asset pricing (Fama and French, 2015), the set of common control variables includes firm size, book-to-market, operating profitability, and investment for measuring benchmark-adjusted returns. Except for MOM, which is updated monthly, the other explanatory variables are updated each June. Furthermore, since we combine firms from multiple countries in the analysis, we include country dummies here and in all subsequent regressions to control for possible country effects.

Table 2 presents average coefficient estimates from the outlined firm-level cross-sectional regression setting for the standard, MAX, and MIN momentum strategies along with difference-of-means tests to assess whether the strategies produce significantly different momentum profits. The last row provides the economic and statistical significance of the average return premiums associated with the three strategies based on the difference between the long and short leg coefficient estimates.

To begin with, specification (1) reports the results for the standard momentum strategy. As indicated by the average coefficient estimates on Long and Short, past winners are associated with significantly positive subsequent returns (1.74% per year), while past losers are associated with subsequent negative returns (-1.83% per year). Though the strategy's short-leg return is statistically somewhat weaker over the sample period, the spread in average returns is sufficient to obtain a significant (long-short) standard momentum premium of 3.57% per year after controlling for firm size, book-to-market, operating profitability, and investment.

[4] For each variable, we use the full SZ, BM, and MOM distribution across all sample firms, so that the stock selection procedure corresponds to independent sorts on the three variables, as in Conrad and Yavuz (2017).

Table 2.2 Benchmark-adjusted returns of standard, MAX, and MIN momentum strategies

	Regression Estimates			Difference-of-Means Tests		
Specification	(1)	(2)	(3)	(2) – (1)	(3) – (1)	(2) – (3)
Strategy	Standard	MAX	MIN			
Long	1.74	3.63	1.65	1.89	-0.09	1.98
	(2.58)	(4.89)	(1.43)	(3.16)	(-0.13)	(2.21)
Short	-1.83	-3.70	0.45	-1.87	2.28	-4.15
	(-1.56)	(-3.20)	(0.52)	(-3.35)	(2.97)	(-4.26)
SZ	-0.37	-0.08	-0.29	0.29	0.08	0.21
	(-1.86)	(-0.34)	(-1.35)	(4.09)	(2.43)	(2.78)
BM	2.96	2.78	3.26	-0.18	0.31	-0.48
	(4.98)	(4.58)	(5.32)	(-2.99)	(2.13)	(-3.36)
OP	1.50	1.55	1.53	0.04	0.02	0.02
	(8.90)	(8.98)	(8.92)	(1.30)	(0.97)	(1.56)
INV	-2.82	-2.82	-2.94	-0.01	-0.12	0.11
	(-4.40)	(-4.29)	(-4.52)	(-0.14)	(-1.71)	(2.73)
R^2	0.14	0.14	0.14			
Long-Short	3.57	7.34	1.20	3.76	-2.38	6.14
	(2.24)	(4.16)	(0.78)	(5.90)	(-3.45)	(6.17)

This table presents average coefficient estimates and associated Newey-West adjusted *t*-statistics (in parentheses) from monthly firm-level cross-sectional regressions along with difference-of-means tests on the average coefficients between the strategies. The dependent variable is the firm's future twelve-month stock return. Long and Short are binary indicator variables that take the value of one if the underlying condition holds for a firm and zero otherwise. Depending on the considered strategy, the conditions are defined as follows. Standard (Long: winner, Short: loser), MAX (Long: small value winner, Short: large growth loser), MIN (Long: large growth winner, Short: small value loser). The classification of firms is based on terciles using the SZ, BM, and MOM distributions. The additional independent variables are firm size (SZ), book-to-market (BM), operating profitability (OP), and investment (INV) and all regressions include country dummies. R^2 is adjusted for degrees of freedom. The last row provides the average return premium associated with the given strategy in percent per year based on the difference between the long and short leg coefficient estimates.

Specifications (2) and (3) report the results for the novel MAX and MIN strategies. When the MAX strategy is considered, where the long leg consists of winners with high expected return characteristics (small and value) and the short leg is based on losers with low expected return characteristics (large and growth), the attainable momentum premium is economically and statistically greatly enhanced and amounts now to more than 7.34% per year. The average return premium is here equally driven by the strategy's long leg (3.63% per year) as well as by the short leg (-3.70% per year). In contrast, when the MIN strategy is considered, where the long leg consists of winners with low expected return characteristics (large and growth) and the short leg is based on losers with high expected return characteristics (small and value), the attainable momentum premium is with its value of 1.20% per year statistically not reliably different from zero.

Comparing our international results to the previous U.S. evidence in Conrad and Yavuz (2017) indicates, in general, a similar return behavior across equity markets. In a related analysis that also controls for the Fama and French (2015) benchmark variables, they report significant MAX momentum premiums of 1.01% per month over the strategy's first six months and 0.59% per month over the subsequent six-month period, which correspond to about 10.03% on an annual basis (formally, $(1+0.0101)^6$ x $(1+0.0059)^6$ - 1) over their 1965-2010 sample period. For the MIN strategy, they report insignificant premiums of 0.11% per month over the first six months and -0.23% over the following six months, which correspond on average to -0.72% per year.

The estimates on the control variables echo in general prior results in the literature and corroborate their importance as cross-sectional return determinants in non-U.S. equity markets. International stock returns are significantly positively associated with book-to-market and operating profitability, while they are significantly negatively related to investment. In contrast, we do not find that firm size has significant power predicting returns during the sample period. This result is, however, also in line with recent international evidence (e.g., Fama and French, 2012, 2017).

The difference-of-means tests in the last three columns show that the average return premiums associated with the MAX and MIN strategies are significantly different from the standard momentum premium and to each other. Relative to the standard strategy, the return spread between winners and losers is noticeably more pronounced when small value winners and large growth losers are considered (MAX), while it is less pronounced when large growth winners and small value losers constitute the strategy (MIN). Finally, the difference between the MAX and MIN momentum premiums is statistically highly significant and amounts to more than 6.14% per year. An inspection of the individual difference-of-means tests reveals that both legs of the MAX strategy significantly contribute to its superior overall performance, regardless of which of the other two strategies is used for comparison.

Since the MAX strategy appears to be the most promising of the three from an investment perspective, we further investigate the strategies' turnover and potential transaction costs to shed light on practical implementation issues. To begin with, though momentum-based investment strategies are often implemented with monthly rebalancing in the literature, we primarily focus in our analysis on the performance over a twelve-month holding period to identify strategies that do not require frequent rebalancing in order to lower transaction costs. Examining the turnover (across the long and short leg portfolios) of the standard, MAX, and MIN momentum strategies in terms of unique stock additions and removals, we find on average values of 33.63%, 39.56%, and 36.67% per year, respectively.[5] However, since we study the strategies based on Fama and MacBeth (1973) regressions which are analogous to creating equal-weighted portfolios, the annual rebalancing to equal weights could potentially increase the turnover to 100% per year.[6] Does this circumstance eliminate the superior performance of the MAX strategy after accounting for corresponding transaction costs?

We address this question by employing the novel insights of Frazzini *et al* (2018) who have analyzed over 1.7 trillion dollars of executed trades across 21 developed equity markets over a 19-year period from AQR Capital, a large institutional asset manager that is well-known for its scientific and factor-based investing approach. Though their cost measures fully take into account bid-ask spreads, market impact costs, and commissions, they find that real-world trading costs are much smaller compared to the – typically assumed – costs used in previous studies.[7] For instance, realized trading costs for long or short positions in non-U.S. stocks are on average 0.11% or 0.22% and range for small stocks from 0.23% (long) to 0.27% (short). Using for simplicity the largest magnitude of 0.27% regardless of the given order type and an annual turnover of 100%, the roundtrip costs would only amount to 0.54% per year which seems negligible in light of the MAX strategy's abnormal return of 7.34% per year.

Up to this point, our full sample results fall right in line with our first hypothesis. To further assess the robustness of our findings across time, firm size, and regions, we repeat our cross-

[5] These magnitudes are similar to the average turnover of value-weighted U.S. momentum strategies (34.5%) that do not rebalance stocks to initial weights (Novy-Marx and Velikov, 2016).
[6] Jegadeesh and Titman (1993) find that even when equal-weighted portfolios are used for momentum strategies, the average turnover is usually less than 100%. They report an average value of 84.8% on their strategy.
[7] The most important determinant of trading costs is the price impact, as bid-ask spreads and trading commissions do not scale with trading size.

sectional regression analysis for the MAX and MIN strategies in two different sub-periods, among small and large firms, and in three different regions (Asia-Pacific, Europe, and Japan). The corresponding results are presented in Table 3, where Panel A shows estimates for the MAX strategy and Panel B shows estimates for the MIN strategy.

Table 2.3 Robustness of MAX and MIN momentum strategies

Panel A: MAX momentum strategy

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	All	All	Small	Large	Asia-Pac	Europe	Japan
Period	Earlier	Later	Full	Full	Full	Full	Full
Long	3.67	3.59	3.19	2.04	1.99	4.34	-1.01
	(3.25)	(4.26)	(3.49)	(2.15)	(0.99)	(4.08)	(-1.41)
Short	-2.53	-4.87	-3.70	-2.66	-7.48	-4.87	-0.39
	(-1.67)	(-3.17)	(-3.43)	(-2.35)	(-4.61)	(-3.36)	(-0.42)
SZ	0.02	-0.17	-1.70	0.57	-1.59	0.28	-0.14
	(0.05)	(-0.92)	(-4.53)	(1.94)	(-2.51)	(1.07)	(-0.38)
BM	3.64	1.93	2.29	3.59	3.91	3.27	4.87
	(3.59)	(4.29)	(4.56)	(4.08)	(3.70)	(3.93)	(5.32)
OP	1.38	1.72	1.44	1.57	6.00	1.44	1.02
	(6.00)	(7.78)	(7.32)	(7.34)	(4.66)	(6.30)	(5.04)
INV	-3.25	-2.40	-2.81	-1.88	-2.29	-2.96	5.57
	(-2.88)	(-5.48)	(-4.10)	(-2.45)	(-2.34)	(-3.73)	(1.41)
R^2	0.16	0.10	0.14	0.16	0.05	0.03	0.04
Long-Short	6.20	8.47	6.89	4.70	9.48	9.21	-0.61
	(2.55)	(3.77)	(4.01)	(2.46)	(2.97)	(3.93)	(-0.46)

Panel B: MIN momentum strategy

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	All	All	Small	Large	Asia-Pac	Europe	Japan
Period	Earlier	Later	Full	Full	Full	Full	Full
Long	1.51	1.79	0.90	0.89	3.99	2.62	-1.94
	(0.86)	(1.38)	(0.90)	(0.89)	(2.58)	(2.24)	(-1.67)
Short	-0.41	1.32	0.55	-0.86	1.44	-1.40	0.81
	(-0.31)	(1.47)	(0.48)	(-0.85)	(0.66)	(-1.25)	(1.00)
SZ	-0.22	-0.36	-2.02	0.36	-1.83	-0.00	-0.04
	(-0.62)	(-2.00)	(-6.01)	(1.41)	(-3.01)	(-0.02)	(-0.11)
BM	4.37	2.15	2.69	4.06	4.08	3.98	4.50
	(4.56)	(3.95)	(5.17)	(4.59)	(3.67)	(4.51)	(4.86)
OP	1.37	1.69	1.44	1.54	5.66	1.40	1.04
	(5.86)	(7.89)	(7.25)	(7.20)	(4.34)	(6.18)	(5.12)
INV	-3.38	-2.50	-2.91	-1.94	-2.52	-3.12	5.36
	(-3.04)	(-5.65)	(-4.27)	(-2.53)	(-2.49)	(-3.94)	(1.39)
R^2	0.16	0.10	0.14	0.16	0.05	0.03	0.05
Long-Short	1.93	0.47	0.35	1.75	2.55	4.03	-2.74
	(0.90)	(0.24)	(0.24)	(1.06)	(1.22)	(2.02)	(-1.72)

This table presents average coefficient estimates and associated Newey-West adjusted *t*-statistics (in parentheses) from monthly firm-level cross-sectional regressions. The dependent variable is the firm's future twelve-month stock return. See Table 2, for a description of the independent variables. R^2 is adjusted for degrees of freedom. The last row provides the average return premium associated with the given strategy in percent per year based on the difference between the long and short leg coefficient estimates. The earlier and later half samples cover July 1990 to December 2003 and January 2004 to June 2017, respectively. The small (large) sub-sample consists of the bottom (top) 50% of firms in each country in terms of market equity, measured as of June of each year. Asia-Pac includes Australia, Hong Kong, New Zealand, and Singapore. With the exception of Japan, Europe encompasses the remaining sample countries (see Panel A of Table 1).

Specifications (1) and (2) report sub-period results. The earlier sub-period runs from July 1990 to December 2003 (162 months), while the later sub-period is from January 2004 to June 2017 (162 months). As documented by the average return premiums on the MAX and MIN strategies, the influence of the expected return characteristics on the realized momentum profits is persistent in the earlier and more recent half of the sample period. The MAX momentum premium is large and significantly present in both sub-periods, while the MIN momentum premium remains insignificant across time.

A further cause for concern for anomalous return patterns is their pervasiveness across size. Though we control for a possible size effect in the cross-section of average returns by including firm size as one of the control variables, it is interesting to know whether our main findings hold across small firms as well as large firms. To address this question, specifications (3) and (4) report size-segmented sub-sample results.[8] The sub-sample of small (large) firms consists of the bottom (top) 50% of firms in each country in terms of market equity, measured as of June of each year. Though the MAX momentum premium is somewhat more pronounced among smaller firms, as it is the case for most other return anomalies, it is not limited to small firms but also significantly present among the largest and economically most important firms in international equity markets. In contrast, we do not find that the MIN strategy produces significant momentum profits among small firms or large firms.

Finally, specifications (5) to (7) provide regional evidence by dividing the EAFE international sample into three major regions in line with Fama and French (2012, 2017). Asia-Pacific includes Australia, Hong Kong, New Zealand, and Singapore. With the exception of Japan, which represents a region of its own, Europe encompasses the remaining sample countries (see Panel A of Table 1). We observe that the MAX momentum premium is strong in terms of economic and statistical significance among Asian-Pacific and European equity markets. On the other hand, we do not find that taking into account expected return characteristics like firm size and book-to-market in the selection of winners and losers produces significant momentum profits in Japan.[9] This result is, however, consistent with Asness (2011) and others who have documented that momentum-based investment strategies do not seem to work among Japanese firms. The regional results for the MIN strategy corroborate in general our international cross-

[8] To be consistent with the intended size segmentation, the MAX and MIN strategies use tercile classifications based on the SZ, BM, and MOM distributions among the bottom or top 50% of firms and not across all sample firms.

[9] In light of this finding, we also have tested whether Japanese firms are influential in our inference that the MAX strategy is superior to the MIN strategy in international equity markets. For instance, the weighting of Japanese firms in the international MAX and MIN strategies could be responsible for the observed return difference. First, the average share of Japanese firms in the long leg portfolios is with values of 25.99% (MAX) and 25.09% (MIN) very similar across the two strategies. Only the short leg portfolios show on average a greater exposure to Japanese firms for the MAX strategy of 37.98% in comparison to 25.16% for the MIN strategy. Second, replicating the performance analysis for the MAX and MIN strategies in an international sample that excludes Japan (EAFE ex Japan) in analogy to Table 2, yields an average MAX momentum premium of 10.23% per year (*t*-statistic of 4.45) and an average MIN momentum premium of 2.24% per year (*t*-statistic of 1.32). Thus, the lack of momentum profits among Japanese firms cannot account for the inference that the MAX strategy is superior to the MIN strategy.

country findings of insignificant momentum profits on this type of strategy. The only exception is Europe, where the MIN momentum premium tends to be statistically significant, but in terms of its economic magnitude, it is still less than half of the corresponding European MAX momentum premium.

After having addressed the robustness of our main findings across time, firm size, and regions, we further study the MAX and MIN momentum premiums conditional upon business conditions. It is well known that the profits of momentum strategies vary with the general state of the economy. They tend to be large during expanding/optimistic states and small during contracting/pessimistic states (Jegadeesh and Titman, 2011). To address whether the MAX and MIN strategies conform to the same pattern observed for standard momentum strategies, we estimate firm-level cross-sectional regressions based on equation (1) for two different specification variants that differ in the underlying state of the economy, i.e., contracting/pessimistic versus expanding/optimistic. We measure the two economic states using six different proxies based on market volatility, market states, investor sentiment, market liquidity, default spread, and the NBER recession indicator. The first two measures are based on international EAFE data, while the remaining measures are based on U.S. data in lack of appropriate cross-country proxies. The use of U.S.-based variables outside the United States can be motivated by Baker *et al* (2012) who show that sentiment is contagious across countries and particularly driven by the U.S. sentiment. Furthermore, Rapach *et al* (2013) document that the United States possesses, as the world's largest and most important equity market, a leading role for international markets.

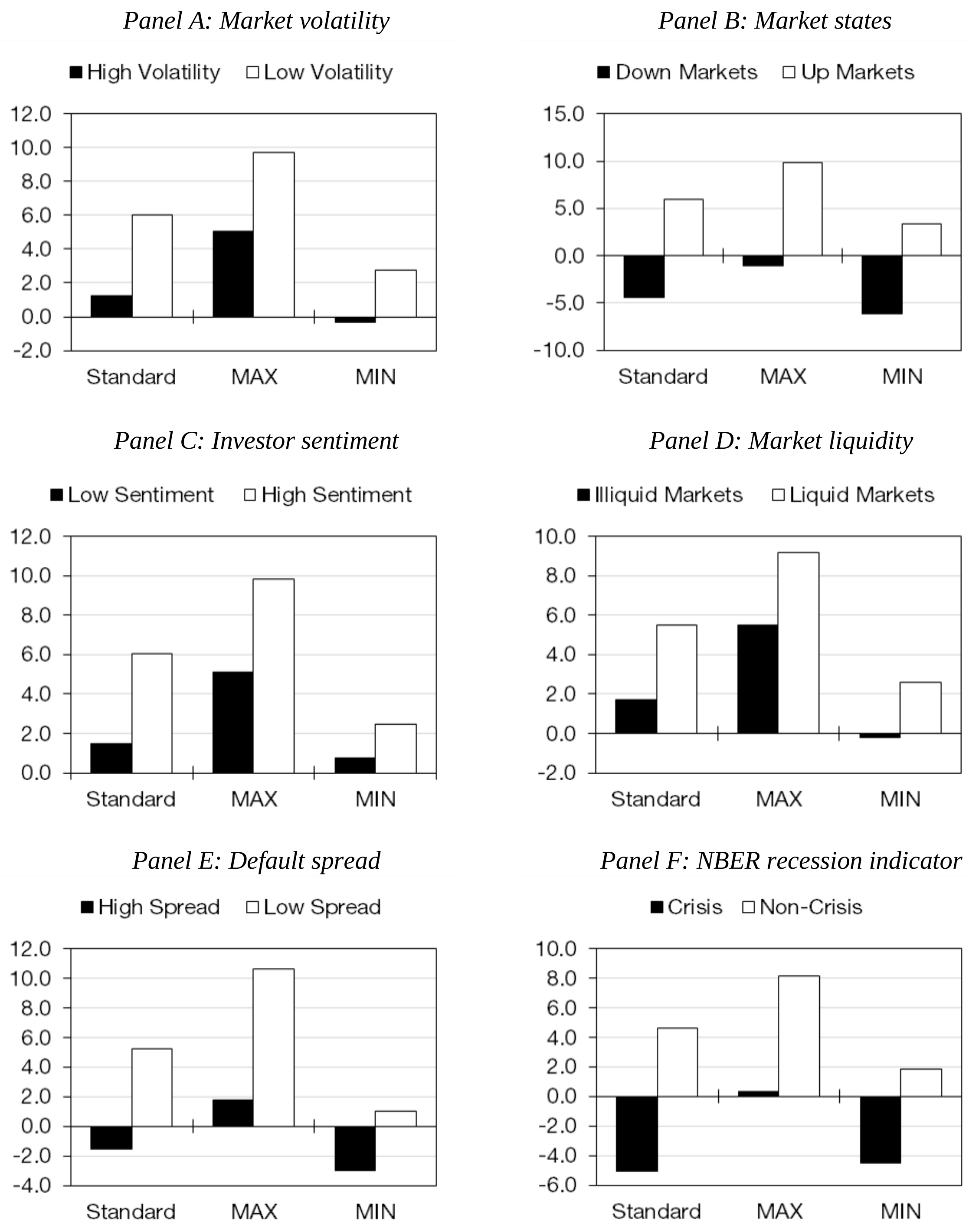
The proxies are defined as follows. Market volatility is the annual standard deviation of the value-weighted EAFE market portfolio returns over the 12 months prior to the beginning of the strategies' holding period (Baker and Wurgler, 2006). Following Cooper *et al* (2004), the market state is measured based on the cumulative return on the value-weighted EAFE market portfolio over the 36 months prior to the beginning of the strategies' holding period. To capture investor sentiment, we rely on the monthly U.S. sentiment index constructed by Baker and Wurgler (2006).[10] To measure market liquidity, we employ Hu *et al*'s (2013) noise index, which is based on the aggregate noise in the prices of U.S. Treasury bonds, i.e., the differences

[10] The sentiment index is available at Jeffrey Wurgler's website: http://pages.stern.nyu.edu/~jwurgler/. The index time series runs until September 2015.

between market and model-implied yields.[11] In light of the fact that the U.S. Treasury bond market is one of the most active and liquid markets in the world and one with the highest credit quality, the level of noise in this market can be used as a market-wide measure of liquidity. In line with Fama and French (1993), the default spread is the monthly difference between the yield on an index of 10-year U.S. corporate bonds and 10-year U.S. Treasury bonds.[12] Finally, the NBER recession indicator for the United States is used to separate crisis from non-crisis periods over the sample period. Except for market states and the NBER recession indicator, the median of the given economic state proxy over the sample period is used to define periods of low and high values on that measure. Positive (negative) 36-month market returns separate up (down) market states.

[11] The noise index is available at Jun Pan's website: http://www.mit.edu/~junpan/. The index time series runs until December 2016. The data is provided on a daily basis. We employ the index's daily end-of-month values for our analysis.
[12] An appropriate U.S. corporate bond index is available in Datastream from April 2002 on.

Figure 2.1 Momentum premiums conditional upon business conditions



This figure illustrates the average return premiums associated with the standard, MAX, and MIN strategies in percent per year during contracting/pessimistic business conditions (black bars) and expanding/optimistic business conditions (clear bars), as measured by six different economic state proxies (Panels A to F).

Figure 1 illustrates the average return premiums associated with the standard, MAX, and MIN momentum strategies during contracting/pessimistic business conditions (black bars) and expanding/optimistic business conditions (clear bars), as measured by the six different economic state proxies (Panels A to F). As before, the premiums are derived from the differences between the long and short leg coefficient estimates from the outlined firm-level cross-sectional regression setting that includes common return controls and country dummies.

First, regardless of the applied economic state proxy, the standard and MAX strategies are associated with significantly positive average return premiums during expanding/optimistic periods. Across the six proxies, the average momentum profits here amount to 5.56% per year on the standard strategy and 9.57% per year on the MAX strategy. During contracting/pessimistic periods, we do, however, not find that the standard and MAX momentum premiums are statistically significantly different from zero. The MIN momentum premium is in general insignificant in both states of the economy. The only two exceptions, where we find significantly positive momentum profits on this type of strategy are periods of low market volatility and after positive 36-month market returns (up markets).

Second, conducting difference-of-means tests on the strategies' average momentum profits during a given economic state corroborates our previous inference on the superiority of the MAX strategy. Regardless of the applied economic state proxy and irrespective of the given economic state, the differences between the MAX and standard momentum premiums are always significantly positive and statistically significant. The same is true for the differences between the MAX and MIN momentum premiums. Hence, the MAX strategy is superior in comparison to the standard and MIN momentum strategies during contracting/pessimistic as well as expanding/optimistic periods. Comparing the MIN strategy relative to the standard strategy, we observe that the differences in premiums are persistently significantly negative during expanding/optimistic periods, while they are in general insignificant during contracting/pessimistic periods.

In sum, the results in this section are consistent with hypothesis H1. Similar to the prior U.S. evidence, we observe that the MAX strategy produces significantly larger benchmark-adjusted returns than the MIN strategy and the standard momentum strategy in non-U.S. equity markets over holding periods up to one year.

2.4 Longer holding period returns

Following the insights of Conrad and Yavuz (2017), we test in this section hypothesis H2 that the MAX strategy displays no return reversal, while the MIN strategy exhibits significant return reversal over holding periods beyond one year. To explore whether their U.S. findings carry over to international equity markets, we estimate different firm-level cross-sectional regressions nested within equation (1), where the dependent variable now is the longer holding period return computed over the second and third year after the measurement of the strategies' underlying firm characteristics.

Table 2.4 Longer holding period returns of MAX and MIN momentum strategies

	MAX momentum strategy		MIN momentum strategy	
Specification	(1)	(2)	(1)	(2)
Return	2nd Year	3rd Year	2nd Year	3rd Year
Long	-0.71	-0.81	-1.45	-1.00
	(-1.08)	(-1.06)	(-1.86)	(-1.50)
Short	0.12	0.72	3.38	2.70
	(0.11)	(0.74)	(4.85)	(4.11)
SZ	-0.25	-0.14	-0.13	-0.02
	(-1.18)	(-0.71)	(-0.64)	(-0.12)
BM	2.14	1.81	1.81	1.54
	(3.81)	(3.15)	(3.32)	(2.98)
OP	1.18	1.09	1.18	1.10
	(7.17)	(5.74)	(7.21)	(5.82)
INV	-1.73	-0.83	-1.72	-0.75
	(-3.20)	(-1.30)	(-3.16)	(-1.18)
R^2	0.13	0.13	0.13	0.13
Long-Short	-0.84	-1.52	-4.83	-3.70
	(-0.52)	(-1.13)	(-4.13)	(-3.59)

This table presents average coefficient estimates and associated Newey-West adjusted *t*-statistics (in parentheses) from monthly firm-level cross-sectional regressions. The dependent variable is the firm's second-year or third-year return after the measurement of the strategies' underlying firm characteristics. See Table 2, for a description of the independent variables. R^2 is adjusted for degrees of freedom. The last row provides the average return premium associated with the given strategy in percent per year based on the difference between the long and short leg coefficient estimates.

Table 4 presents average coefficient estimates from the outlined firm-level cross-sectional regression for the two year-to-year holding periods. The results document that selecting winners and losers conditional upon their expected return characteristics based on firm size and book-to-market also has a major impact on the behavior of longer holding period returns.

While the MAX strategy yields strong momentum profits in the first year (see Table 2), it does not display significant return reversals in the following two years. The average coefficient estimates on Long and Short as well as the resulting (long-short) MAX momentum premium are all statistically indistinguishable from zero. This is in sharp contrast to the MIN strategy which does not produce significant momentum profits in the first year but suffers from substantial return reversals in the subsequent years. The average MIN momentum premium is -4.83% per year in the second year and -3.70% in the third year. As indicated by significantly positive short-leg returns, the reversal is primarily driven by the rebound of the strategy's short leg that generates benchmark-adjusted returns of around 3% per year.

Taken together, the results in this section strongly support hypothesis H2. Short-term return continuation and long-term return reversals are not necessarily linked. Taking into account expected return characteristics like firm size and book-to-market in the selection of winners and losers helps to *ex ante* separate momentum stocks that display return reversals from those that do not.

2.5 A mispricing-based explanation

In this section, we test our final hypothesis H3 that the strong performance of the MAX strategy and the weak performance of the MIN strategy are the outcome of mispricing. Even though Conrad and Yavuz (2017) argue in favor of a risk-based explanation, they do not rule out the possibility that the varying MAX and MIN momentum premiums may be attributable to cross-sectional mispricing. In particular, they only study whether the U.S. premiums are related to market states and investor sentiment. Lagged market returns and the investor sentiment index are commonly used as market-wide proxies for mispricing that reflect aggregate investor confidence or risk aversion which may cause delayed overreaction among investors and therefore provide an explanation for the observed momentum pattern in average stock returns. However, both explanations fall short to explain the MAX and MIN momentum premiums. Though the level of market-wide mispricing may explain the varying strength of the momentum premium across time, existing mispricing at one point in time can also vary across firms (Hirshleifer and Jiang, 2010; Walkshäusl, 2016).

Following this reasoning, we explicitly investigate the aspect of cross-sectional mispricing as an explanation for the significantly different return behavior of the MAX and MIN strategies. To proxy for systematic mispricing, we employ the firm's external financing behavior as measured by Bradshaw *et al*'s (2006) XFIN variable. Positive values on XFIN indicate issues, while negative values indicate repurchases. The opportunistic financing hypothesis (Ikenberry *et al*, 1995; Loughran and Ritter, 1995) suggests that firms issue additional capital when prices are high and repurchase outstanding capital when prices are low. Thus, issues (repurchases) provide signals of potential overvaluation (undervaluation) based on the management's private assessment of the firm's intrinsic value relative to the market. Thus, if cross-sectional mispricing drives the return behavior of the MAX and MIN strategies, the realized momentum profits on the two strategies should consequently differ when the underlying momentum stocks are either perceived as overvalued or undervalued.

To examine whether the observed return premiums on the MAX and MIN strategies are attributable to the systematic exploitation of cross-sectional mispricing, we estimate firm-level cross-sectional regressions based on equation (1) for two different specification variants that differ in their underlying stock samples. Specification (1) excludes winners that are also issuers and losers that are also repurchasers, thus, representing overvalued winners and undervalued losers. Specification (2) excludes winners that are also repurchasers and losers that are also issuers, thus, denoting undervalued winners and overvalued losers. The firms excluded from the corresponding samples are identified each month by their monthly-updated MOM characteristic and their XFIN characteristic which is measured each June. By constraining the underlying stock samples in this way, we obtain groups of firms, where the perceived mispricing of winners and losers is in general favorable (specification (1)) or unfavorable (specification (2)) for momentum strategies that exploit cross-sectional mispricing.

Table 2.5 Returns to MAX and MIN momentum strategies conditional on mispricing

Specification	(1)			(2)		
Excluding	Overvalued winners & undervalued losers			Undervalued winners & overvalued losers		
Return	1st Year	2nd Year	3rd Year	1st Year	2nd Year	3rd Year
Panel A: MAX momentum strategy						
Long	6.29	1.94	0.37	1.41	-2.26	-3.41
	(5.66)	(1.90)	(0.33)	(1.29)	(-2.84)	(-3.26)
Short	-5.75	-2.93	-1.35	-1.57	1.60	1.47
	(-4.70)	(-2.33)	(-1.11)	(-1.33)	(1.41)	(1.81)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.13	0.12	0.12	0.12	0.12	0.12
Long-Short	12.04	4.87	1.73	2.98	-3.86	-4.88
	(5.51)	(2.47)	(0.88)	(1.56)	(-2.47)	(-3.42)
Panel B: MIN momentum strategy						
Long	2.73	0.21	0.07	0.58	-2.87	-1.66
	(2.94)	(0.31)	(0.10)	(0.47)	(-3.31)	(-1.83)
Short	-2.13	1.61	2.22	1.80	5.80	4.79
	(-1.39)	(1.23)	(1.52)	(1.25)	(4.81)	(5.03)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.13	0.12	0.12	0.12	0.13	0.12
Long-Short	4.85	-1.40	-2.15	-1.21	-8.67	-6.45
	(2.56)	(-0.85)	(-1.32)	(-0.63)	(-5.74)	(-5.46)

This table presents average coefficient estimates and associated Newey-West adjusted *t*-statistics (in parentheses) from monthly firm-level cross-sectional regressions. The dependent variable is the firm's first-year, second-year or third-year return after the measurement of the strategies' underlying firm characteristics. The common control variables are untabulated, see Table 2, for a description. The sample in specification (1) excludes overvalued winners and undervalued losers, while the sample in specification (2) excludes undervalued winners and overvalued losers. Misvaluation is identified by the firm's external financing behavior, where negative values on XFIN denote undervaluation and positive values on XFIN denote overvaluation. R^2 is adjusted for degrees of freedom. The last row provides the average return premium associated with the given strategy in percent per year based on the difference between the long and short leg coefficient estimates.

Table 5 presents average coefficient estimates from the two outlined firm-level cross-sectional regression variants using holding period returns computed over the first, second, and third year after the measurement of the strategies' underlying firm characteristics. Panel A shows estimates for the MAX strategy and Panel B shows estimates for the MIN strategy. For the sake of brevity, the estimates on the common control variables are not tabulated.

The results document that cross-sectional mispricing plays an important role in understanding the return behavior of MAX and MIN strategies. In line with our previous findings, the MAX strategy produces a significantly positive momentum premium in the first year and no significant return reversals in the following two years when the unfavorably-mispriced winners and losers are excluded from the sample (specification (1)). However, this inference changes considerably when the favorably-mispriced winners and losers are left out. In specification (2), the MAX momentum premium is rendered insignificant in the first year, and the strategy now suffers from substantial return reversals in the second and third year.

Analogously, the previously found poor performance of the MIN strategy turns strong when the unfavorably-mispriced winners and losers are excluded from the sample, as done in specification (1). The strategy then yields significantly positive momentum profits in the first year and exhibits no significant return reversals in the subsequent years. In contrast, when the favorably-mispriced winners and losers are discarded in specification (2), the MIN strategy reveals its weak performance with strong return reversals in the second and third year.

Taken together, the results in this section strongly support hypothesis H3. The realization of the superior performance on the MAX strategy and the occurrence of the inferior performance on the MIN strategy is strongly dependent on cross-sectional mispricing. The varying performance of the MAX and MIN strategies among favorably-mispriced and unfavorably-mispriced winners and losers furthermore suggests that firm size and book-to-market may rather be proxies for cross-sectional mispricing than risk-based expected return characteristics.

2.6 Conclusion

In this paper, we test the U.S. findings of Conrad and Yavuz (2017) that stocks with momentum can be *ex ante* separated from those that exhibit reversal by taking into account characteristics like firm size and book-to-market in the selection of winners and losers. We provide strongly supportive out-of-sample evidence on the previous U.S. findings in the broad cross-section of international firms drawn from 20 developed non-U.S. equity markets over the sample period from 1990 to 2017.

A strategy that buys small value winners and sells large growth losers, denoted the MAX strategy, generates significantly larger momentum profits than a standard momentum strategy, is robust to common return controls, and does not suffer from return reversals for holding periods up to three years. In contrast, a strategy that buys large growth winners and sells small value losers, denoted the MIN strategy, produces no significant momentum profits but significant return reversals over holding periods beyond one year. Consistent with the view that firm size and book-to-market can also be interpreted as measures of mispricing, the significantly different return behavior of the MIN and MAX strategies is attributable to a rather systematic exploitation of cross-sectional mispricing among momentum stocks. The superior performance of the MAX strategy is driven by undervalued winners and overvalued losers, while the inferior performance of the MIN strategy is driven by the fact that the strategy's underlying stock selection procedure picks overvalued winners and undervalued losers.

Chapter 3

Overnight Returns: An International Sentiment Measure

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Abstract The suitability of overnight returns as a firm-specific investor sentiment measure, previously found in the United States, is similarly present in international equity markets. This delivers a completely novel approach to measure investor sentiment at the firm level. For applicability reasons overnight returns have to fulfill 3 characteristics that would be expected of a sentiment measure. First, overnight returns persist in the short run; second, this persistence is stronger among harder-to-value firms; and third, stocks with high overnight returns underperform in the long run. Implementing this novel sentiment measure on a common anomaly, the authors find explanatory power even beyond a market-wide sentiment measure.

Keywords Investor sentiment, Overnight returns, International markets, Asset pricing, Behavioral finance

3.1 Introduction

It is well established that sentiment plays a substantial role in stock markets all around the globe. A broad set of literature focuses on this topic and mainly concentrate on market-wide investor sentiment (Brown and Cliff [2004], Baker and Wurgler [2006], Stambaugh, Yu, and Yuan [2012]). However, international sentiment literature is scarce and no established sentiment measure for international stock markets is available so far (Baker, Wurgler, and Yuan [2012]). In a recent study on the U.S. stock market, Aboody, Even-Tov, Lehavy, and Trueman [2018] find strong evidence that overnight returns function as a measure of firm-specific investor sentiment. In particular, they document that overnight returns possess characteristics that would be expected for a sentiment measure at the firm level and present affirmative results for the price reaction to earnings announcements.

Early findings by Lee, Shleifer and Thaler [1991] and Barber, Odean, and Zhu [2009] examine that retail investors are the ones be most affected by sentiment. In connection with Berkman, Koch, Tuttle, and Zhang [2012] who demonstrate that retail investors tend to place their orders outside the opening hours of stock exchanges the potential application of overnight returns as a firm-specific sentiment measure can be motivated. In detail, orders placed when stock markets are closed will be executed at the start of the next trading day. This leads to increased price pressure at the open, rather lower prices during the rest of the trading day and finally higher overnight returns. Berkman et al. [2012] show that high-attention days for individual stocks (e.g. strong absolute returns or strong retail buying) are followed by high demand near the opening of the next trading day.[13]

Branch and Ma [2006] already find similar results and demonstrate that the correlation between overnight returns and subsequent intraday returns is negative but argue that this is due to manipulation on the part of market makers. However, Cliff, Cooper, and Gulen [2008] contradict this thesis and assume that algorithmic trading could be the source of the observed return effect. Likewise later work by Kelly and Clark [2011] argue in favor of a behavioral approach and show that the risk premium is negative intraday while it is positive overnight and trace it on undiversified active traders. Finally Berkman et al. [2012] extend these debates providing evidence that attention-triggered buying of individual investors at the open offers a combining

[13] Barber and Odean [2008] show that individual investors are more likely to purchase stocks that have a higher attention level (E.g. stocks that are in the news, with high trading volume, or with high absolute returns).

approach for this behavior. Furthermore, they demonstrate that these return patterns are even stronger among stocks that are objectively harder-to-value.

The findings of Aboody et al. [2018] that overnight returns function as a measure of sentiment are interesting especially for international stock markets for three reasons. First, overall there is no ubiquitous sentiment measure available at the firm level, where most of the literature focuses on market-wide sentiment.[14] In their seminal work, Aboody et al. [2018] provide evidence that overnight returns proxy for firm-specific investor sentiment on the U.S. equity market. Second, literature that focuses on international stock markets has to use U.S. sentiment measures as proxies for international sentiment (Walkshäusl [2016]).[15] This is due to the lack of a universally valid sentiment measure for international markets and based on the findings of Baker et al. [2012] that international investor sentiment is transferable and partially driven by US sentiment.[16] Third, compared to the well-known and most applied sentiment measure of Baker and Wurgler [2006], the method proposed by Aboody et al. [2018] does not require special datatypes. For instance, Baker and Wurgler [2006] use the exclusive datasets for IPOs from Jay Ritter's website, which delivers data primarily for the U.S. market.

In this paper, we contribute to the literature by studying the suitability of overnight returns as a firm-specific investor sentiment measure in the broad cross-section of an international sample outside the United States. Our cross-sectional test setting has two advantages compared to a time-series test setting. First, we can directly examine the effect of overnight returns at the firm-level leaving out possible portfolio effects. Second, conventional time-series test settings to calculate abnormal returns are based on close-to-close returns, whereas we examine overnight returns. However, a cross-sectional test setting allows us to easily control for various return determinants typically used in asset pricing literature. Finding evidence would be a substantial contribution for international sentiment literature, as overnight returns could be used as a direct sentiment measure on any examined equity market. Therefore, sentiment for international markets could be determined at the firm-level and no proxies would be necessary.

[14] See, e.g. Baker and Wurgler [2006], Arif and Lee [2014], Gao and Süss [2015], Huang, Jiang, Tu and Zhou [2015], and Stambaugh, Yu, and Yuan [2012].

[15] Eun and Lee [2010] argue that markets around the globe have become more integrated and Rapach, Strauss and Zhou [2013] show that the USA plays a leading role for international markets.

[16] As a direct measure is not available so far, Schmeling [2009] use consumer confidence as a proxy for the investor sentiment on international markets.

Furthermore, as with every finding in empirical research, the suitability of overnight returns as a firm-specific sentiment measure could be the result of data snooping in the meaning of Lo and MacKinlay [1990] and as a consequence be sample-specific. In order to counteract this concern, we examine the suitability of overnight returns as a measure of firm-specific sentiment in the broad cross-section of international firms. Since international stocks provide a new sample, this non-American survey provides a useful out-of-sample test on global markets. Observing similar results to the recent U.S. evidence in Aboody et al. [2018] would strengthen their findings and the importance of overnight returns in a behavioral context. That may also lead to a better understanding of overnight returns around the globe and extends the application scope for a firm-specific sentiment measure to international equity markets.

Specifically, derived from Aboody et al. [2018] we test the following three hypotheses out-of-sample in international stock markets. Finding supporting evidence for all of the three hypotheses is necessary to confirm the suitability of overnight returns as a firm-specific sentiment measure.

The first hypothesis addresses the short-run persistence of overnight returns. According to Barber et al. [2009], the investment behavior of retail investors is strongly affected by sentiment. They conclude that a disparity in orders of retail investors remains persistent over subsequent weeks. Taking into account that Berkman et al. [2012] show that retail investors tend to place orders outside the opening hours of stock exchanges, overnight returns should remain similarly persistent over several weeks.

Hypothesis 1: *Firms with high overnight returns yield significantly positive risk-adjusted returns in the short-run.*

Our second hypothesis is motivated by the findings of Baker and Wurgler [2006]. They show that market-wide sentiment has a greater impact on firms that are objectively harder-to-value. Further literature also shows that sentiment affects the returns of firms that are harder to value more, than firms that are easier to value. [17]

Specifically, in line with Aboody et al. [2018] we test the short run persistence for five harder-to-value measures, namely size, book-to-market ratio, operating profitability, volatility and age.

[17] See e.g. Berkman, Dimitrov, Jain, Koch and Tice [2009], Hirbar and McInnis [2012], and Seybert and Yang [2012].

For the validity of the assumption, the overnight return persistence should be stronger among firms that are objectively harder-to-value.

Hypothesis 2: *The short-run overnight return persistence is significantly higher for harder-to-value firms.*

The third hypothesis addresses the long-term underperformance of stocks with high demand from retail investors in the short-run. This assumption is based on the findings of Hvidkjaer [2008] and Barber et al. [2009], who show that stocks with high short-term demand from retail investors underperform those stocks with relatively low short-term demand. This temporary mispricing is a characteristic what is expected of a sentiment measure. Even Baker and Wurgler [2006] argue that stocks with more attention from optimistic traders earn lower returns over the subsequent 12 months. Therefore, the returns in the long-run should be smaller among the firms with high overnight returns.

Hypothesis 3: *Stocks with high overnight returns yields significantly smaller risk-adjusted returns in the long-run.*

Our results are easily summarized. Similar to the United States, overnight returns are suitable as an international measure for firm-specific investor sentiment. First, we find a significant and positive overnight return persistence for about four weeks or longer after portfolio formation that cannot be explained by established return predictors of the cross-section. Second, the overnight return persistence is considerable larger among firms that are harder to value, even though we control for common risk factors. Thus, the effect is stronger for firms that are smaller, have a high book-to-market ratio, a low profitability, a high volatility or have a younger age. Third, stocks with high overnight returns in the short run obtain negative total returns in the long run and vice versa.

Taken together, our out-of-sample analysis strongly supports the findings in Aboody et al. [2018]. Hence, the overnight return effect and consequently its applicability as a firm-specific sentiment measure seems to be a phenomenon across stock markets.

The remainder of the paper is organized as follows. Section 2 describes the data and variables used in this study. Section 3 examines the short-run persistence of overnight returns. Section 4 investigates whether the observed return behavior is stronger among harder-to-value firms.

Section 5 studies the long-term behavior of stocks with strong overnight returns in the short run. Section 6 presents application results and Section 7 concludes the paper.

3.2 Data and Variables

We study an international country sample that consists of firms from 20 developed non-U.S. equity markets: Australia, Austria, Belgium, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland and the United Kingdom. The sample selection mirrors the countries included in the famous Europe, Australia and the Far East (EAFE) stock market benchmark form MSCI that measures stock market performance outside of North America. We collect daily closing and opening prices on common stocks from Datastream and firm-level accounting information (e.g. book equity) from Worldscope. We calculate the daily close-to-close (total) return, $r^i_{close-to-close,t}$, using standard total return prices. The intraday return, $r^i_{intraday,t}$, is the return between the opening and closing of the same day t. Given that Datastream provides total return prices only for the close, we calculate intraday returns with adjusted opening and closing prices in line with the methodology proposed by Lou et al. [2017]. Therefore, we assume that dividend adjustments that could move share prices occur overnight.[18] The overnight return is then calculated as the deviation between close-to-close and intraday return.

$$r^i_{intraday,t} = \frac{P^i_t}{PO^i_t} - 1 \qquad (1)$$

where P^i_t is the closing price for the shares of firm i on day t, and PO^i_t is the opening price for the shares on day t.

$$r^i_{close-to-close,t} = \frac{RI^i_t}{RI^i_{t-1}} - 1 \qquad (2)$$

where RI^i_t is the total return closing price for the shares of firm i on day t, and RI^i_{t-1} is the total return closing price for the shares on day t - 1.

[18] Results are similar when we use local currencies.

$$r^i_{overnight,t} = \frac{1 + r^i_{close-to-close,t}}{1 + r^i_{intraday,t}} - 1 \qquad (3)$$

Following Lou et al. [2017], we then calculate the weekly overnight returns, taking the compounded daily overnight return starting on Wednesday of week w - 1 and ending on Tuesday of week w.[19] The weekly close-to-close return is calculated by the same method.

To ensure that accounting information is known before the returns are calculated, we match the latest accounting information for the fiscal year ending in the previous calendar year with stock returns from the first week in July (~ week 27) of the current year to the end of June (~ week 26) of the subsequent year throughout the paper. All data are denominated in U.S. dollars.[20] To ensure that our results are not driven by tiny or illiquid stocks, we follow Ang, Hodrick, Xing, and Zhang [2009] and exclude very small firms by eliminating the 5 per cent of firms with the lowest market equity in each country. Furthermore, as in Fama and French [1992] firm-year observations with negative book equity are excluded from the sample. Due to the fact that most of the countries have reported opening prices since 1992, our sample period starts in the first week of July in 1992 and ends in the last week of June 2017.

Panel A of Table 1 reports a summary statistic for the countries included in the international sample. On average our sample includes 7918 firms, where the largest portion falls on the countries Japan and the United Kingdom.

The variables used in this study are defined as follows. Beta (BETA) is estimated relative to all stocks using 5years (60 months) of past returns. A firm's size (SZ) is its stock price multiplied by the number of shares outstanding, calculated as of the end of every month in million U.S. dollars. Book-to-market (BM) is the ratio of book equity to market equity at the fiscal year-end. Momentum (MOM) is the cumulative prior six-month stock return, skipping the most recent month (Jegadeesh and Titman [1993]). Following Fama and French [2015], investment (INV) is the annual change in total assets divided by lagged total assets. Operating profitability (OP) is revenues minus cost of goods sold and interest expense, all divided by book equity. Age (AGE) is the number of years since a company was founded. In line with Aboody et al. [2018]

[19] Beginning on Wednesday is consistent with Lehmann [1990] and Barber et al. [2009].

[20] We have also redone all calculations with local currencies and gain very similar results.

volatility (VOL) is calculated as the standard deviation of monthly stock returns for the prior twelve-month stock return, skipping the most recent month.

Table 3.1 Summary Statistics

Panel A: Sample Countries

Country	Firms	Country	Firms
Australia	720	Japan	2804
Austria	38	Netherlands	121
Belgium	86	New Zealand	72
Denmark	93	Norway	129
Finland	111	Portugal	38
France	460	Singapore	307
Germany	464	Spain	113
Hong Kong	621	Sweden	254
Ireland	23	Switzerland	176
Italy	205	United Kingdom	1083

Panel B: Variables

Variable	Mean	25^{th}	Median	75th
BETA	0.92	0.51	0.86	1.26
SZ	1273.32	55.03	171.81	670.42
BM	0.98	0.43	0.75	1.24
MOM	0.06	-0.14	0.02	0.20
OP	0.72	0.23	0.50	0.90
INV	0.16	-0.05	0.05	0.17
AGE	38.61	15.96	33.99	58.61
VOL	0.38	0.23	0.32	0.47

This table shows summary statistics for the countries included in the international (EAFE) sample and the variables used in this study. Panel A reports the average number of firms in each country over the sample period from July 1992 to June 2017. For the most part of the sample data is available since 1992 namely, Australia, Austria, Belgium, Denmark, France, Germany, Italy, Japan, Netherlands, Portugal, Singapore, Spain, Switzerland, United Kingdom. For the rest of the sample data history for opening prices starts later, specifically Finland (2001/03), Hong Kong (1994/06), Ireland (1999/01), New Zealand (1996/02), Norway (1995/12), and Sweden (2001/06). Panel B reports the mean, 25th percentile, median, and 75th percentile of the variables. Beta (BETA) is estimated relative to all stocks using 60 months of past returns. Size (SZ) is market equity (stock price multiplied by the number of shares outstanding) at the end of the previous month. Book-to-market (BM) is the ratio of book equity to market equity for the fiscal year ending in the previous calendar year. Momentum (MOM) is the cumulative prior six-month stock return, skipping the most recent month. Operating profitability (OP) is revenues minus cost of goods sold and interest expense, all divided by book equity. Investment (INV) is the annual change in total assets divided by total assets. Age (AGE) is the number of years since the firms' foundation (calculated as of the end of each month). Volatility (VOL) is the standard deviation of prior twelve-month stock return, skipping the most recent month.

Panel B of Table 1 presents a summary statistic for variables used in this study. Focusing on the key variables of interest that moreover serve as our hard-to-value measures, we observe that a typical firm in our sample has an average size of $ 1.273 million, an average book-to-market ratio of 0.98 and a mean operating profitability of 0.72. The age of firms exhibits a mean (median) of 38.61 (33.99) years and the mean (median) volatility is 38% (32%) among the whole sample.

3.3 Short-Term Persistence in Overnight Returns

In this section, we test Hypothesis 1 that firms with high overnight returns yield significantly positive overnight returns in the short run. We first present the baseline results for our international sample and further examine the robustness of our main findings with respect to common control variables and different subsamples.

Baseline results

To obtain a first impression of the persistence of overnight returns, we begin our analysis at the portfolio level. In particular, each Wednesday, we form quintile portfolios by sorting stocks based on their overnight return of week w. We then calculate the subsequent average weekly overnight returns for the following weeks w + 1 up to week w + 4.

Table 3.2 Persistence of Weekly Overnight Returns and Related Weekly Close-to-Close Returns

Panel A: Persistence of Overnight Returns

	Average weekly overnight return			
Quintiles OVN Returns	Week w + 1	Week w + 2	Week w + 3	Week w + 4
1	-0.91	-0.79	-0.73	-0.69
2	-0.00	0.04	0.04	0.04
3	0.20	0.20	0.20	0.19
4	0.42	0.37	0.36	0.36
5	0.95	0.79	0.73	0.72
(5) – (1)	1.86	1.58	1.46	1.41
	(37.90)	(40.26)	(33.29)	(35.23)

Panel B: Behavior of Related Close-to-Close Returns

	Average weekly close-to-close return			
Quintiles OVN Returns	Week w + 1	Week w + 2	Week w + 3	Week w + 4
1	0.24	0.16	0.14	0.15
2	0.21	0.19	0.17	0.19
3	0.21	0.19	0.20	0.19
4	0.21	0.19	0.20	0.19
5	0.10	0.15	0.16	0.19
(5) – (1)	-0.14	-0.01	0.02	0.04
	(-4.19)	(-0.37)	(0.93)	(1.24)

This table presents average weekly overnight and close-to-close returns for week w + 1 through w + 4. The weekly overnight returns on the stock of firm i during week w is the accumulated daily overnight return beginning on Wednesday of week w – 1 and ending on Tuesday of week w. The weekly close-to-close return for week w is the compounded daily return over the period beginning on Wednesday of week w – 1 and ending on Tuesday of week w. We rank all stocks each week in ascending order according to their overnight return that week and partition the stocks into quintiles. Panel A reports the average weekly overnight return over the subsequent 4 weeks for the stocks in each quintile. The last row provides the average spread return between firms with high and low overnight return. Panel B reports the average weekly close-to-close return. The Newey-West adjusted t-statistic is given in parentheses.

Table 2 presents average weekly returns for quintile portfolios sorted on overnight returns. Panel A of Table 2 shows associated overnight returns for subsequent weeks. While the lowest quintile displays -0.91% for week w + 1 the quintile with the highest past overnight returns displays 0.95% in week w + 1. Accordingly, this yields a highly significant positive return of 1.86% for the high minus low portfolio in week w + 1. The long-short return decreases slightly during the following weeks; however it is still strong and significant in week w + 4 (1.41%). Thus, we note that a long-short strategy based on past overnight returns produces significant return differences over the following weeks. These findings are in line with the U.S. findings by Aboody et al. [2018].

For a comprehensive picture, we calculate the average weekly close-to-close (total) returns for the quintile portfolios for week w + 1 through week w + 4 (Panel B of Table 2). Unlike the overnight returns, the weekly total returns are not persistent throughout the weeks. Week w + 1 displays a slightly negative return premium for the long-short strategy (-0.14%), week w + 2 through week w + 4 yield no significant return results. Interestingly, the insignificant long-short portfolio returns seem to be the outcome of strong returns in the lowest portfolio, compared to

Panel A of Table 2. To sum up, overnight returns have no predictive power for short term total returns. These findings are also in line with Aboody et al. [2018] who could not find steady total returns within the U.S. equity market either.

Common risk factors and robustness

Portfolio sorts represent a very useful approach to investigate how average returns vary with different levels of overnight returns. However, as it is of particular interest whether overnight returns can be used as a sentiment measure at the firm level, we now study the overnight return persistence at the individual firm level using the Fama and MacBeth [1973] methodology, which provides a test setting that easily allows for multiple control variables.

In particular, we estimate a weekly cross-sectional regression of average weekly overnight returns in conjunction with common controls. Furthermore, we introduce a high (low) indicator variable that is equal to one if the firm's overnight return of week w falls in the top (bottom) 20 per cent of all stocks and zero otherwise. Following Fama and French [2015], the set of common control variables includes beta (BETA), firm size (SZ), book-to-market (BM), operating profitability (OP), investment (INV) and momentum (MOM). The explanatory variables are either updated at the end of each June (BETA, SZ, BM, OP, INV) or weekly (MOM) to predict weekly overnight returns.

Table 3.3 Cross-Sectional Regressions of Weekly Overnight Returns on Overnight Return Indicators and Common Controls

Panel A: Overnight Return Persistence throughout Subsequent Weeks

	Week w + 1	Week w + 2	Week w+ 3	Week w + 4
High	0.73	0.58	0.50	0.52
	(25.74)	(23.20)	(22.17)	(24.15)
Low	-1.05	-0.90	-0.81	-0.78
	(-26.65)	(-27.00)	(-23.92)	(-25.05)
BETA	0.19	0.20	0.20	0.20
	(10.73)	(11.95)	(12.12)	(11.67)
SZ	0.03	0.03	0.04	0.04
	(3.06)	(4.02)	(4.29)	(4.13)
BM	-0.06	-0.07	-0.07	-0.08
	(-4.29)	(-5.23)	(-5.48)	(-5.81)
OP	0.01	0.00	0.00	0.00
	(1.12)	(0.80)	(0.75)	(0.86)
INV	0.01	0.02	0.02	0.02
	(0.78)	(1.39)	(1.15)	(1.16)
MOM	-0.51	-0.28	-0.22	-0.16
	(-5.51)	(-4.14)	(-3.63)	(-2.86)
R^2	0.08	0.07	0.07	0.07
High-Low	1.77	1.47	1.32	1.30
	(32.51)	(34.63)	(29.71)	(33.82)

Panel B: Robustness of Overnight Return Persistence

	Earlier	Later	Europe	Asia Pacific	Japan
High	0.94	0.54	1.16	0.65	0.20
	(26.08)	(27.97)	(12.52)	(18.22)	(15.68)
Low	-1.03	-1.06	-1.49	-1.44	-0.35
	(-14.83)	(-25.97)	(-25.42)	(-17.06)	(-18.38)
BETA	-0.03	0.13	0.17	0.17	0.16
	(-3.19)	(6.24)	(12.66)	(8.57)	(5.06)
SZ	-0.03	0.08	0.06	0.05	0.01
	(-3.19)	(10.06)	(5.14)	(5.21)	(0.52)
BM	-0.00	-0.11	0.01	-0.32	0.02
	(-0.10)	(-9.44)	(0.56)	(-12.99)	(1.48)
OP	0.04	-0.02	-0.00	-0.03	0.03
	(5.53)	(-4.38)	(-0.22)	(-0.95)	(7.26)
INV	-0.06	0.09	0.02	0.12	-0.12
	(-2.12)	(7.12)	(1.25)	(6.02)	(-3.46)
MOM	-0.94	-0.12	-0.50	-0.12	-1.16
	(-8.90)	(-1.06)	(-6.17)	(-0.95)	(-9.00)
R^2	0.09	0.06	0.05	0.06	0.04
High-Low	1.97	1.59	2.65	2.09	0.54
	(21.15)	(31.76)	(19.71)	(23.67)	(23.08)

This table presents average coefficient estimates and associated Newey-West adjusted *t*-statistics (in parentheses) from weekly firm-level cross-sectional regressions. The dependent variable is the firm's future weekly overnight stock return. The overnight return indicator high (low) is equal to one if the firm's weekly overnight return is in the top (bottom) 20 per cent during the formation week w, and zero otherwise. The independent variables are beta (BETA), firm size (SZ), book-to-market (BM), operating profitability (OP), investment (INV), and momentum (MOM). All regressions include country dummies. In the regressions, SZ and BM are measured in natural logs. R^2 is adjusted for degrees of freedom. The last row provides the average return premium in percent per week based on the difference between the high and low coefficient estimates. Panel A reports results for short-run persistence for week w + 1 through week w + 4. Panel B reports robustness results for week w + 1. The earlier and later half samples cover July 1992 to June 2004 and July 2004 to June 2017, respectively. Europe includes Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. Asia Pacific encompasses the remaining sample countries excluding Japan (see Table 1).

Panel A of Table 3 presents average coefficient estimates for weeks w + 1 to w + 4 within the outlined weekly firm-level cross-sectional regression to assess the persistence of the long-short premium across time. The last row provides the economic and statistical significance of the average high-low returns reporting the difference between the high and low coefficient estimates.

Beginning with week w + 1, we find a significant positive coefficient estimate on the high indicator of 0.73 per cent per week while the low indicator is significantly negative at -1.05 per cent. This leads to a highly significant and large high-low premium of 1.77 per cent per week (t-statistic 32.51) in the first week. Similar to Panel A of Table 2, the returns decline constantly throughout the subsequent weeks but are still strong (1.30%) in week 4.

Given that we examine weekly overnight returns, our results deviate from effects observed in a standard cross-sectional regression setting. Panel A of table 3 shows overnight returns load positive on beta (0.19%) as well as on size (0.05%) in week w + 1 and stay almost unchanged throughout the weeks. The returns load significantly negative on book-to-market in every single week. Operating profitability appears to be slightly positive but us insignificant over the observed period. The estimated coefficient for investment is insignificant and close to zero for the observed period. Finally, the returns load significantly negative on momentum especially for week w + 1 (-0.51%) and halve in the subsequent weeks but the premium still stays significantly negative. The negative momentum premium seems to be a consequence of bid-ask spread and price pressure that appears in the very short term (Jegadeesh and Titman [1993]). Taken together in the very short term overnight returns load positive on size and profitability while they load negative on book-to-market and momentum.

The previous findings strongly support Hypothesis 1 that overnight returns are persistent in the short-run. Nevertheless, to ensure that our results are robust, Panel B of Table 3 presents average coefficient estimates for week w + 1 for different sub-samples to assess the pervasiveness of overnight returns across different sample periods and different regions.[21] To address how persistent the observed effect is over time we divide our sample into two sub-periods. The earlier sub-period is from the first week in July in 1992 to the last week in June in 2004, while the

[21] As the results for subsequent weeks stay almost unchanged, for clarity we only present results for week w + 1 here.

later sub-period is from the beginning of July in 2004 to end of June in 2017. As shown in the last row of Panel B, the return premium of overnight returns is economically sustainable and statistically highly significant in both sub-periods. Whereas the premium is slightly stronger in the earlier (1.88%) period, it still yields 1.54% in the more recent half of the sample period.[22]

The Europe subsample yields a tremendously positive premium of 2.65 per cent per month in the first week after portfolio formation. A significantly positive high indicator (1.16%) as well as a significantly negative low indicator (-1.49%) equally drive the premium. Following Fama and French [2012], we divide the Asia subsample in Japan and Asia Pacific (including Australia, New Zealand, Hong Kong, and Singapore). Similar to the European sample the Asia Pacific sample performs quite well and leads to a positive premium of 2.09 per cent for the first week. As expected from momentum studies on the Japanese equity market, the premium for the Japan sub-sample is considerable weaker.[23] This might be due to missing individualism as described by Chui, Titman, and Wei [2010] or it might be simple due to chance as argued by Fama and French [2012]. Nevertheless, in contrast to a standard momentum approach on the Japanese equity market, overnight returns still amount to a significant positive premium of 0.54 per cent for the first week after portfolio formation.

In sum, the results in this section strongly support Hypothesis 1. Similar to the prior U.S. evidence, we observe a significant persistence of overnight returns, that cannot be explained by established cross-sectional return determinants, and that is robust within different sub-periods and regions.

[22] We have also redone the calculations for a subsample from 2007-2008 comprising the global financial crisis. While the Low coefficient is more pronounced during this period, the premium is quite similar as among the full sample period.
[23] Asness, Moskowitz, and Pedersen [2013] and Fama and French [2012] find no momentum premium in Japan following a standard momentum approach.

3.4 Higher Spread for HTV Firms

Baker and Wurgler [2006] already concluded that sentiment has greater impacts on considerably harder-to-value firms.[24] Therefore, we test whether the overnight return pervasiveness is even stronger for harder-to-value firms in our Hypothesis 2. Finding this would support that overnight returns can be used as an international measure for sentiment. Following Aboody et al. [2018], we use five harder-to-value characteristics, namely firm size, book-to-market, profitability, volatility, and age.[25] Consistent with previous literature, firms that are small, have a high book-to-market ratio (as a proxy for growth opportunities), are less profitable, have a high stock return volatility or are young are harder to value.[26]

Table 3.4 Cross-Sectional Regressions of Weekly Overnight Returns and Hard-to-Value Proxies

Panel A: Cross-Sectional Regressions of Weekly Overnight Returns and HTV Proxies without Controls

	SIZE	BM	OP	VOL	AGE
OVN	0.13	0.14	0.14	0.14	0.13
	(65.11)	(38.19)	(33.26)	(43.80)	(33.93)
OVNxDHTV	0.04	0.02	0.02	0.02	0.06
	(4.28)	(3.83)	(6.71)	(4.97)	(9.09)
SZ	0.05				
	(5.32)				
BM		-0.07			
		(-9.76)			
OP			0.02		
			(6.48)		
VOL				0.21	
				(2.45)	
AGE					0.20
					(7.11)
R^2	0.09	0.09	0.08	0.09	0.09

[24] Other references: Hribar and McInnis [2012] and Seybert and Yang [2012].
[25] We use book-to-market instead of earnings-to-price, as it is more common in literature as a measure of growth (e.g. Fama and French [2012]).
[26] For example Baker and Wurgler [2006], Mian and Sankaraguruswamy [2012] and Seybert and Yang [2012], also use at least one of these characteristics as a hard-to-value proxy.

Panel B: Cross-Sectional Regressions of Weekly Overnight Returns and HTV Proxies with Controls

	SIZE	BM	OP	VOL	AGE
OVN	0.13	0.15	0.14	0.14	0.14
	(61.43)	(36.40)	(30.82)	(38.66)	(31.22)
OVNxDHTV	0.06	0.02	0.02	0.02	0.07
	(4.22)	(2.49)	(7.35)	(4.82)	(10.08)
BETA	0.17	0.16	0.16	0.13	0.16
	(9.85)	(9.80)	(9.83)	(10.31)	(9.22)
SZ	0.04	0.04	0.04	0.05	0.03
	(4.90)	(4.20)	(4.29)	(6.43)	(3.59)
BM	-0.06	-0.06	-0.05	-0.05	-0.04
	(-4.49)	(-5.02)	(-4.03)	(-4.29)	(-2.69)
OP	0.01	0.01	0.01	0.01	0.02
	(1.28)	(1.47)	(1.76)	(1.38)	(3.54)
INV	0.02	0.02	0.02	0.02	0.02
	(1.16)	(1.05)	(1.02)	(1.08)	(1.45)
MOM	-0.54	-0.55	-0.56	-0.58	-0.56
	(-6.39)	(-6.32)	(-6.38)	(-6.52)	(-7.12)
VOL				0.31	
				(4.86)	
AGE					0.16
					(7.30)
R^2	0.09	0.09	0.09	0.09	0.09

This table presents average coefficient estimates and associated Newey-West adjusted *t*-statistics (in parentheses) from weekly firm-level cross-sectional regressions. The dependent variable is the firm's overnight return in week w + 1. See Table 3, for a description of the independent variables. OVN is the firm's overnight return of week w. DHTV is a dummy variable based on the corresponding harder-to-value characteristic namely size, book-to-market, operating profitability, volatility and age. For size (SIZE), operating profitability (OP) and age (AGE) the dummy (DHTV) is one if the characteristic is above 75 % and zero otherwise. For book-to-market (BM) and volatility (VOL) the dummy is one if the characteristic is below 25 % and zero otherwise. In the regressions, SZ and BM are measured in natural logs. R^2 is adjusted for degrees of freedom. Panel A reports results for the previous overnight return (OVN), the interaction term (OVNxDHTV) and the specific harder-to-value characteristic. Panel B contains additional results for the full set of independent controls (see Table 3).

To test how the overnight returns vary between firms with different levels of hard-to-value characteristics, we proceed as follows. We estimate cross-sectional regressions of weekly overnight returns for week w + 1 on the overnight return of week w without control variables (Panel A of Table 4) and with the full set of control variables as outlined in Table 3 (Panel B of Table 4). To study the relation between overnight returns and the harder-to-value characteristics, we take the above mentioned harder-to-value characteristics into account. Furthermore, we employ an interaction term between overnight returns (OVN) and a dummy variable (DHTV) that equals one if a firm is objectively harder-to-value and zero otherwise. The interaction terms capture the differential overnight return effects regarding the particular hard-to-value characteristic.

For size the related dummy variable is one if a firm's size (SZ) is in the bottom quartile and zero otherwise. Dummy variables for profitability (OP) and age (AGE) are constructed accordingly and become one if the characteristic is in the bottom quartile of profitability or age respectively, and zero otherwise. The dummy variable for book-to-market (BM) and volatility (VOL) equals one if the variable is in the top quartile and zero otherwise. The interaction term (OVNxDHTV) is then the overnight return (OVN) of week w multiplied with the determined harder-to-value dummy (DHTV). Thus, the average coefficient estimate on the interaction term provides the economic difference of the overnight returns between firms with high levels of harder-to-value characteristics and the residual firms.

Based on the previous findings in the literature and the alignment of our dummy variables, we expect positive estimates on every single interaction term between overnight returns and the hard-to-value characteristic to confirm Hypothesis 2. Therefore, the overnight return persistence should be stronger among firms that are objectively harder-to-value.

Table 4 presents average coefficient estimates from the outlined weekly cross-sectional regressions for each of our five hard-to-value measures. For brevity, we only report results for week w + 1.[27] We provide results that control only for the respective harder-to-value characteristic in Panel A of Table 4, and for robustness concerns, additionally control for the full set of common controls in Panel B of Table 4. All reported regressions include country dummies. Inferences are, however, very similar when country dummies are omitted.

First, analyzing Panel A of Table 4, as indicated by significantly positive values on size, profitability, volatility and age, firms that load on these measures have higher future overnight returns. The coefficient estimate on book-to-market is negative, which implicates a negative return relation between the book-to-market ratio and future overnight returns. Nevertheless, controlling for the harder-to-value characteristics does not drive out the overnight return persistence

[27] The results remain very similar throughout week w + 2 to week w + 4.

in the cross-section of overnight returns. In fact, OVN remains an economically and statistically highly significant predictor for future overnight returns across all variables.

The signs on the interaction terms are consistent with our above-mentioned predictions. Every single interaction term between OVN and the hard-to-value dummy variable is significantly positive. These findings suggest that the positive overnight return persistence is stronger among firms that are objectively harder-to-value. In detail, for size, the average OVN coefficient estimate is 0.13 and the interaction term carries a value of 0.04 (t-statistic = 4.28). Hence, the results imply that the OVN return persistence is larger and statistically significant among smaller firms with an estimate of 0.17 (formally, 0.13 + 0.04). For book-to-market, the overnight coefficient estimate is 0.14 and the interaction term amounts to 0.02 (t-statistic = 3.83). Therefore, the results conclude that firms with a higher book-to-market have a greater overnight return persistence. Firms with low profitability have a higher overnight return persistence manifested in a positive interaction term of 0.02 (t-statistic = 6.71). The overnight returns persistence turns out to be stronger among more volatile firms with an estimate of 0.16 (formally, 0.14 + 0.02). Finally, the results for age display that the effect is stronger among younger firms, with an estimate of the interaction term of 0.06 (t-statistic = 9.09).

Panel B of Table 4 includes common controls as further robustness checks of the stronger overnight return persistence among harder-to-value firms in the cross-sectional regression, namely beta, size, book-to-market, profitability, investment, and momentum as well as the particular harder-to-value characteristic if not already included in the common controls (VOL & AGE). The interactions and dummy variables operate in the same way as in Panel A of Table 4. The results obtained correspond qualitatively to those presented in Panel A and thus lead to the same inferences. Even with several control variables the results for each of the harder-to-value characteristics remain economically and statistically significant; thus the overnight return persistence is stronger among firms that are harder to value.

In summary, the results in this section strongly support Hypothesis 2. Similar to the results of prior U.S. studies, the short-term overnight return persistence is stronger among firms that are harder to value, which provides further evidence that overnight returns are suitable as a firm-specific investor sentiment measure.

3.5 Long-Term Reversal

In this section, we test Hypothesis 3, that in the long-run stocks with high overnight returns significantly underperform those with low overnight returns. In other words, we shed light on the long-term return behavior of stocks with high and low overnight returns during the formation period. This reflects the third requirement for the usability of overnight returns as a measure of firm-specific sentiment. Aboody et al. [2018] document for the U.S. equity market that for the first year after portfolio formation based on the monthly overnight returns of December, the close-to-close return is significantly lower in the top decile than in the bottom decile. Therefore, we test in the following whether these findings also occur in our non-U.S. sample.

Table 3.5 Cross-Sectional Regressions for Longer Holding Period Close-to-Close Returns

Panel A: Cross-Sectional Regressions of Close-to-Close Returns without Controls

	Year 1	Year 2	Year 3
High	-0.50	-0.09	-0.39
	(-0.70)	(-0.13)	(-0.75)
Low	0.26	1.78	1.34
	(0.33)	(2.30)	(2.11)
R^2	0.09	0.09	0.09
High-Low	-0.76	-1.87	-1.73
	(-2.26)	(-3.64)	(-3.53)

Panel B: Cross-Sectional Regressions of Close-to-Close Returns with Controls

	Year 1	Year 2	Year 3
High	-0.98	-0.13	-0.25
	(-2.31)	(-0.29)	(-0.71)
Low	-0.47	1.08	1.02
	(-0.90)	(1.80)	(1.89)
BETA	-0.48	-0.55	0.56
	(-0.71)	(-0.87)	(0.65)
SZ	-0.66	-0.18	-0.08
	(-2.36)	(-0.74)	(-0.36)
BM	3.12	1.96	1.59
	(4.48)	(3.59)	(3.39)
OP	1.58	1.28	1.24
	(7.42)	(5.77)	(5.35)
INV	-2.11	-1.40	-1.27
	(-2.34)	(-1.85)	(-1.48)
MOM	4.16	-4.37	-1.27
	(1.59)	(-3.10)	(-1.00)
R^2	0.11	0.10	0.10
High-Low	-0.51	-1.21	-1.27
	-1.00	-2.07	-2.34

This table presents average coefficient estimates and associated Newey-West adjusted *t*-statistics (in parentheses) from monthly firm-level cross-sectional regressions. The dependent variable is the firm's first-year, second-year or third-year return after the portfolio formation. High (low) indicator is equal to one if a firm's past monthly overnight return is in the top (bottom) 20 per cent and zero otherwise. See Table 3 for a description of the independent variables. In the regressions, SZ and BM are measured in natural logs. R^2 is adjusted for degrees of freedom. The last row provides the average return premium. Panel A reports results for the high and low indicators without controls and Panel B reports results for the full set of independent controls (see Table 3).

We estimate monthly cross-sectional regressions of overlapping yearly close-to-close returns without control variables (Panel A of Table 5) and with the full set of the previously employed control variables that are either updated at the end of each June (BETA, SZ, BM, OP, INV) or monthly (MOM). The additional high (low) indicator is equal to one if the firm's overnight return of the past month is in the top (bottom) 20 per cent and zero otherwise. Our observation period starts in July 1992 and ends in June 2017.

Panel A of Table 5 presents average coefficient estimates from the outlined monthly firm-level cross-sectional regression of overlapping yearly returns without controls to assess the long-run close-to-close return behavior. The last row provides the economic and statistical significance of the average return premium by reporting the difference between the high and low coefficient estimates. We find a significant negative premium of -0.76 for the first year, which is driven by a negative high indicator (-0.50 %) and a positive low indicator (0.26 %). The high-low premium stays significantly negative up to three years after portfolio formation and becomes insignificant thereafter.

Panel B of Table 5 includes the common controls as further robustness tests. The premium is insignificant for year one but significantly negative for years two and three after formation. Interestingly, the return on the high indicator is significantly negative for year one and diminishes in the following years.

Table 5 provides insights into the long-run of close-to-close returns sorted on past overnight returns. In sum, the results support our Hypothesis 3 that stocks with high overnight returns yield significantly smaller risk-adjusted returns in the long-run. These results indicate a potential overpricing of firms with high overnight returns in the short-run compared to those with low overnight returns. Thus, our international results strongly confirm the findings of Aboody et al. [2018] and previous literature by Hvidkjaer [2008] or Barber et al [2009] in favor of temporary mispricing.

3.6 Application Test

In this section, we use the firm-specific investor sentiment measure to examine the explanatory power in the context of the momentum anomaly motivated by recent empirical evidence. Using the well-known sentiment index of Baker and Wurgler [2006], Antoniou, Doukas and Subrahmanyam [2013] show that momentum is strongly affected by market-wide sentiment.[28] This provides an ideal test-setting to not just examine whether overnight returns affect momentum in a similar way, but also to test the firm-specific sentiment character of overnight returns by analyzing the explanatory power beyond market-wide sentiment. Following Antoniou et al. [2013], we define momentum as the cumulative returns from month t - 7 to t - 2 and present results for holding periods of six months and 12 months as well as the period from month 13 to 24 after formation.

[28] Stambaugh et al. [2012] also provide similar results.

To study the relation between momentum and overnight returns, we employ a momentum control variable (MOM) and a dummy variable (HOVN) that is one if a firm's overnight return is in the top quintile during the formation month, and zero otherwise. As prior studies have shown, we expect a positive momentum effect for up to twelve months within our international sample, that turns negative in year two (Jegadeesh and Titman [1993]). If the overnight returns are suitable as a firm-specific sentiment measure we expect a significantly negative interaction term between momentum and the high overnight return dummy. In order to examine whether overnight returns have explanatory power beyond market-wide sentiment, we split our sample into two subsamples relating to the BW sentiment measure following Stambaugh et al. [2012]. [29] They suggest a high-sentiment month is one when the value of the measure in the previous month is about the median and zero otherwise. Thus, we have a subsample of high sentiment including 140 months of the observations period and a second subsample including 140 months of low sentiment.[30]

Table 3.6 Cross-Sectional Regressions of Momentum Conditional on Sentiment

Panel A: Cross-Sectional Regressions of Momentum without Controls

	Full			Low BW Sentiment			High BW Sentiment		
	6 Mo	Year 1	Year 2	6 Mo	Year 1	Year 2	6 Mo	Year 1	Year 2
Momentum	4.79	5.43	-4.84	2.37	-0.31	-2.80	7.29	11.62	-6.79
	(2.66)	(2.02)	(-2.80)	(0.75)	(-0.07)	(-1.86)	(4.53)	(5.06)	(-2.41)
MOMxHOVN	-2.06	-3.17	0.51	-2.59	-2.90	-0.87	-1.69	-3.55	1.83
	(-3.18)	(-3.58)	(0.54)	(-3.14)	(-3.05)	(-1.01)	(-1.87)	(-2.40)	(1.25)
R^2	0.11	0.10	0.10	0.08	0.06	0.06	0.15	0.15	0.13

[29] The sentiment index is on Wurgler's website: http://pages.stern.nyu.edu/jwurgler/.
[30] Given that data for Wurgler's sentiment is only available until 09/2015 the observation period in this section ends in the same month.

Panel B: Cross-Sectional Regressions of Momentum with Controls

	Full			Low BW Sentiment			High BW Sentiment		
	6 Mo	Year 1	Year 2	6 Mo	Year 1	Year 2	6 Mo	Year 1	Year 2
Momentum	4.07	5.31	-4.85	2.17	0.38	-3.73	5.90	10.61	-5.91
	(2.35)	(2.04)	(-3.26)	(0.69)	(0.09)	(-2.33)	(4.26)	(5.14)	(-2.58)
MOMxHOVN	-2.17	-3.57	0.91	-2.66	-3.89	-0.52	-1.67	-3.09	2.27
	(-3.83)	(-4.55)	(0.98)	(-3.37)	(-3.83)	(-0.60)	(-2.06)	(-2.47)	(1.59)
BETA	-0.26	-0.65	-0.57	0.09	-0.06	-1.30	-0.86	-1.60	0.14
	(-0.55)	(-0.95)	(-0.88)	(0.12)	(-0.05)	(-2.15)	(-1.73)	(-2.68)	(0.14)
SZ	-0.28	-0.65	-0.20	-0.54	-1.24	-0.09	0.09	0.01	-0.31
	(-1.60)	(-2.27)	(-0.79)	(-2.38)	(-3.36)	(-0.32)	(0.38)	(0.04)	(-0.84)
BM	1.75	3.10	1.98	0.60	1.13	2.46	3.01	5.07	1.49
	(4.53)	(4.46)	(3.66)	(1.50)	(1.54)	(4.23)	(5.52)	(5.35)	(2.08)
OP	0.76	1.57	1.28	0.75	1.61	1.33	0.80	1.51	1.22
	(6.54)	(7.47)	(5.73)	(4.08)	(5.17)	(5.05)	(6.57)	(6.83)	(4.18)
INV	-1.65	-2.17	-1.37	-0.59	-0.73	-2.63	-2.59	-3.24	-0.15
	(-3.70)	(-2.37)	(-1.83)	(-0.92)	(-0.54)	(-4.89)	(-5.11)	(-3.35)	(-0.12)
R^2	0.12	0.11	0.10	0.08	0.06	0.06	0.16	0.16	0.13

This table presents average coefficient estimates and associated Newey-West adjusted *t*-statistics (in parentheses) from monthly firm-level cross-sectional regressions. The dependent variable is the firm's six-month, first-year or second-year return after the portfolio formation. Momentum is the cumulative prior six-month stock return, skipping the most recent month. HOVN is a dummy variable based on the monthly overnight return in the formation month. HOVN is equal to one if a firm's overnight return is in the top 20 % for a given month and zero otherwise. The full sample covers the whole observation period (see Table 1). Low (high) BW sentiment samples cover all month with a Baker and Wurgler sentiment value in the previous month below (above) the median of all months between July 1992 and September 2015. In the regressions, SZ and BM are measured in natural logs. R^2 is adjusted for degrees of freedom. Panel A reports results for momentum and the interaction term (MOMxHOVN). Panel B contains additional results for the full set of independent controls (see Table 3).

Table 6 presents average coefficient estimates from the outlined monthly cross-sectional regressions for our momentum measure. In Panel A of Table 6 we provide results that control only for momentum and for the full set of common controls in Panel B.

Analyzing the full Period of Panel A in Table 6, we find a significant momentum for a six-month (4.79%) holding period as well as for a twelve-month (5.43%) holding period that turns negative in year 2 (-4.84%). For six- and for twelve-months our interaction (MOMxHOVN) is significantly negative (-2.08% for six-months and -3.17% for twelve-months), these results show that our firm-specific international sentiment measure has explanatory power for the momentum anomaly. Specifically, stocks with a high past overnight return have a significantly negative impact on the momentum premium.

To test whether the firm-specific sentiment measure has explanatory power above and beyond the already known sentiment measures we take a closer look at the two subsamples here. First, analyzing the periods with low BW sentiment, we find that there is no momentum for the observed periods but our firm-specific measure is still significantly negative within the 6- and 12-months periods.[31] Thus, even in cycles of low BW sentiment, we find that our measure has predictive power and yields significantly negative future returns for overpriced stocks. Second, periods of high BW sentiment display strong and highly significant momentum returns within the international sample but even in this subsample we have a negative interaction term of -1.69% for the first six months that leads towards significance (t-statistic of -1.87) and a significantly negative value for the 12-month period of -3.55% (t-statistic of -2.40). These results demonstrate that even in a positive market-wide BW sentiment, a firm-specific sentiment can determine mispriced stocks.

For the sake of completeness, we also provide results with the full set of common controls in Panel B of Table 6. The results are briefly summarized and strongly correspond with the results of Panel A. Our international firm-specific sentiment measure has predictive power for six-month and 12 month holding periods among the full observation period as well as the two subsamples.

Taken together, the results in this section strongly support the suitability of overnight returns as a sentiment measure and demonstrate the practical applicability of a firm-specific investor sentiment measure.

[31] In line with prior U.S. findings of Antoniou et al. [2013], they find that momentum arises only in positive sentiment periods.

3.7 Conclusion

In this paper, we study the suitability of overnight returns as a firm-specific sentiment measure in equity markets outside the United States. We provide strongly supportive out-of-sample evidence on the previous U.S. findings by Aboody et al. [2018] using a broad sample of international equity markets during the time period 1992-2017.

To verify the suitability of overnight returns as a firm-specific sentiment measure three requirements have to be fulfilled. First, we find pervasive evidence of significant persistence in overnight returns in the short-run even after controlling for a large set of established return predictors, such as beta, firm size, book-to-market, profitability, investment, and momentum. Second, studying the observed overnight return persistence in combination with harder-to-value characteristics, we find that the persistence is stronger among firms that are objectively harder to value. Specifically, we follow Aboody et al. [2018] and categorize stocks that are small, have a high book-to-market ratio (as a measure of growth), a low profitability, a high past return volatility, or are young as harder-to-value. The third condition is that stocks with high overnight returns show a long-term reversal in close-to-close returns. For a period of up to three years, stocks with high short-term overnight returns yield significantly negative returns in comparison to stocks with low overnight returns, this corroborates a mispricing-based explanation.

Implementing overnight returns as a firm-specific sentiment measure within the momentum anomaly, we provide evidence that our sentiment measure possesses predictive power above and beyond the well-known market-wide sentiment index by Baker and Wurgler [2006]. As a result, this study delivers a practicable method to measure firm-specific investor sentiment even outside the United States.

Chapter 4
Continuing Overreaction: European Evidence

This research paper is joint work with Florian Weißofner. The paper has been submitted to the Quarterly Review of Economics and Finance and is currently under review. The journal ranking is B according to the VHB JOURQUAL 3 (2015) journal quality list.

Abstract This paper tests Byun, Liam and Yun (2016) continuing overreaction measure using weighted signed volumes in European equity markets. As in the U.S., firms with high measures of continuing overreaction outperforms firms with low measures. The observed premium is even higher than within a standard momentum approach and does not suffer from return reversal for holding periods up to three years. Furthermore, the observed premium is robust to common controls, such as firm size, book-to-market and momentum, as well as more recent controls for investment and operating profitability. Within different business conditions, the novel measure has clear superiority towards momentum especially during contracting/pessimistic periods.

Keywords Momentum, Trading volume, Return predictability,
Continuing overreaction, International markets

4.1 Introduction

It is well established that overconfidence can explain a broad set of anomalies all around the globe. Specifically, the research goes back to Daniel, Hirshleifer, and Subrahmanyam (1998), who demonstrate that the overconfidence of investors and their biased self-attribution can explain overreactions as well as underreactions in international stock markets. They argue that in the course of overestimation of their own abilities investors overvalue private information and underreact to public information signals. However, if a later public signal confirms the private information thus good (bad) news supports the investor’s buy (sell) decision, his confidence rises and leads to biased self-attribution. Or to put it in a simple way: past returns predict future returns, and as a consequence short-run momentum and long-term reversals arise.[32]

Building upon the insight that continuing overreaction causes momentum in the short run, Byun, Liam and Yun (2016) construct a completely novel measure of continuing overreaction (CO hereafter). They argue if CO causes momentum as argued by Daniel et al. (1998) a more direct CO measure can predict future returns better than past returns and the results are even stronger within stocks held primarily by investors leaning towards biased self-attribution. To calculate the continuing overreaction measure they use weighted signed volumes and the direction of investor’s overreaction indicated by the sign of stock returns.

The results of Byun et al. (2016) are interesting especially for two reasons. First, the premium based on the innovative continuing overreaction measure is economically significant and actually larger than the premium of a standard momentum approach. The CO premium stays significant even when they control for momentum while inversely momentum disappears when CO is taken into account. In addition, in line with prior momentum literature (e.g. Asness 2011) they cannot find significant CO premium for the Japanese equity market due to missing biased self-attribution. Second, Byun et al. (2016) provide a direct support of the Daniel et al. (1998) model that overconfidence and biased self-attribution leads to overreactions and a better estimation of stock return predictability.

[32] For the well-known momentum effect on the U.S. equity market see Jegadessh and Timan (1993, 2001) and e.g. Rouwenhorst (1998), Chui, Titman and Wei (2010) or Asness, Moskowitz and Pedersen (2013) for non-U.S. evidence.

A broad set of literature already demonstrated theoretical evidence that overconfidence leads to higher trading volume. Odean (1998) demonstrates that trading volume increases when investors are overconfident and described it as the most robust effect of overconfidence.[33] Barber and Odean (2001) provide empirical evidence that men are more overconfident than women are and thus trade more excessively. Furthermore, Statman, Thorley and Vorking (2006) also find supporting evidence on the theoretical models of higher trading volume as a result of biased self-attribution by Gervais and Odean (2001).[34]

Byun et al. (2016) argue that trading volume can be used as a proxy for overconfidence, but the trading volume itself does not predict future stock returns, because the direction of overreaction is not known. Therefore, they multiply the trading volume with the sign of the average stock return in the given time period. Specifically, if the stock return is negative (positive) the signed volume has a negative (positive) sign as well. Additionally, Byun et al. (2016) take the weighted sum of signed volumes and simultaneously give a larger weight the more recent the signed volume is to the point where CO is calculated.[35] As a consequence, the novel CO measure displays a trend of investor overconfidence in the examined time.

Given that the study mentioned above mainly focuses on the U.S. equity market, but momentum and continuing overreaction is also present outside the USA (Rouwenhorst, 1998; Chui, Titman and Wei, 2010; Fama and French, 2012; Asness, Moskowitz and Pedersen,2013), we contribute in the present paper on the literature by studying the novel CO measure in European equity markets for the first time. As with any finding in empirical research, the CO measure could be the result of data snooping in the sense of Lo and MacKinlay (1990) and therefore be sample specific. Given that empirical financial research mostly focuses on the U.S. market (Karolyi, 2016), testing former U.S. results in non-U.S. markets is important to enhance the quality of the return predictability literature as well as to guard against data snooping. To address this concern, we independently examine in this study the relation between CO measures and subsequent stock returns in the broad cross-section of European firms drawn from 15 developed non-

[33] Benos (1998) also exhibits a theoretical model where the trading volume increases with the number of overconfident traders in the stock market.
[34] For further empirical evidence see e.g. Glaser and Weber (2009) and Grinblatt and Keloharju (2009).
[35] Statman et al. (2006) also use signed volume and examine it within a time series test setting.

U.S. equity markets. As European equity markets provide fresh data, our non-U.S. analysis provides a useful out-of-sample test on the significance of the CO measure around the world.

Following the previous US evidence, we develop three hypotheses that we test out-of-sample in foreign European equity markets. The first hypothesis addresses whether European stock market returns sorted on the innovative CO measure conform to the same pattern observed in the United Sates.

Hypothesis 1: A *significantly positive relation exists between the firm's continuing overreaction measure and subsequent stock returns.*

Showing that a positive return relation exists between firms with high CO measures and firms with low CO does not, however, rule out the possibility that the identified return behavior is simply a manifestation of already known return effects. Therefore, we examine in the second hypothesis whether the return effect is pervasive in the presence of various return predictors.

Hypothesis 2: *The return difference between firms with the strongest CO measure and firms with the lowest CO measure is not subsumed by established cross-sectional determinants.*

On the one hand, we control for the traditional return effects based on firm size and book-to-market (Fama and French 1992). Taking into account the most recent developments in asset pricing on the other hand, we also control for the novel benchmark variables associated with operating profitability and investment that have been proposed by Fama and French (2015) for a comprehensive description of the cross-section of average stock returns. Besides that, we also test whether a momentum factor (Jegadeesh and Titman 1993) drives out the observed premium.

Hypothesis 3: *The return premium between firms with high and low CO measures is also present within different business conditions.*

As it is well known that momentum profits vary with the state of the economy, we test the CO measure in contracting/pessimistic business conditions and compare it to expanding/optimistic business conditions. As different measures, we use market volatility, market states, investor sentiment, market liquidity, default spread, and the NBER recession indicator.

Our results are easily summarized. Similar to the United States, the CO measure is suitable as an international measure for continuing overreaction. First, we find a significant and positive return premium between stocks with high and low CO measures for about one year after portfolio formation that becomes insignificant afterwards but does not turn into reversal. Second, the return premium cannot be explained by established cross-sectional determinates and even a momentum factor cannot explain the premium. Third, CO premium is also available during different states of the economy.

Taken together, our out-of-sample analysis strongly supports the CO measure constructed by Byun et al. (2016). The continuing overreaction measure provides a newly and more direct measure even on the European stock markets. Furthermore, the results improve the quality of literature regarding return predictability in the sense of Daniel et al. (1998) across equity markets.

The remainder of the paper is organized as follows. The next section describes the data and variables used in this study. The subsequent sections test the outlined hypotheses and present the empirical results. The final section concludes the paper.

4.2 Data and summary statistics

We study a European stock market sample that consists of firms from fifteen developed markets: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. Our sample selection mirrors the countries included in the well-known European stock market benchmark form MSCI. We collect monthly total return data on common stocks from Datastream and firm-level accounting information from Worldscope. To make sure that accounting information is known before the returns are calculated, we match the latest accounting information for the fiscal year ending in the previous year with stock returns from July of the current year to June of the subsequent year. All data are denominated in U.S. dollars. To ensure that our results are not driven by tiny or illiquid tocks, we follow Ang et al. (2009) and exclude the 5% of firms with the lowest market equity in each country. In addition, as in Fama and French (1992) firm-year observations with negative book equity are excluded from the sample as well as financial firms with Standard Industrial Classification (SIC) codes between 6000 and 6999. The sample period is from July 1990 to June 2018.

Following Byun et al. (2016) we calculate the continuing overreaction measure as follows. The signed volume ($SV_{i,t}$) for stock i in month t is defined as the sum of the trading volume which is the number of shares traded in month i multiplied by the stock price. Furthermore, $r_{i,t}$ is the stock return for firm i in the given month t.

$$\mathrm{SV_{i,t}} = \begin{cases} \mathrm{TV_{i,t}} & \text{if } r_{i,t} > 0, \\ 0 & \text{if } r_{i,t} = 0, \\ -\mathrm{TV_{i,t}} & \text{if } r_{i,t} < 0 \end{cases} \tag{1}$$

To calculate CO, in line with Byun et al. (2016) we assign increasing weights to signed volumes that means the more recent a month the higher the weight of the signed volume. In detail, as we use a 1-year formation period for CO calculation throughout the paper, the weight for the most recent month is 12 while the penultimate month is weighted with 11 and so forth until month t-12 that is one year ago and therefore weighted with 1. We normalize the signed volume, taking the sum of the weighted values and divide it by the average trading volume over the same period of 12 months.

$$\mathrm{CO_{i,t}} = \frac{\mathrm{sum}(\mathrm{w_j} * \mathrm{SV_{i,t-J}}, \dots, \mathrm{w_1} * \mathrm{SV_{i,t-1}})}{\mathrm{mean}(\mathrm{VOL_{i,t-J}}, \dots, \mathrm{VOL_{i,t-1}})} \tag{2}$$

Panel A of Table 1 reports the total number of firm-year observations for the countries included in the European sample. On average, our sample includes 3407 firms. In line with their importance for the European stock market, the largest portion falls on the countries UK, France, and Germany.

The variables used in this study are defined as follows. A firm's size (SZ) is its stock price multiplied by the number of shares outstanding, calculated as of the end of every month in million U.S. dollars. Book-to-market (BM) is the ratio of book equity to market equity at the fiscal year-end. Momentum (MOM) is the cumulative prior twelve-month stock return, skipping the most recent month (Jegadeesh and Titman, 1993). Following Fama and French (2015), investment (INV) is the annual change in total assets divided by lagged total assets. Operating profitability (OP) is revenues minus cost of goods sold and interest expense, all divided by book equity.

Table 4.1 Summary statistics, 1990-2018

Panel A: Sample countries

Country	Firms	Country	Firms
Austria	56	Netherlands	109
Belgium	79	Norway	114
Denmark	97	Portugal	49
Finland	85	Spain	98
France	530	Sweden	233
Germany	523	Switzerland	144
Ireland	39	United Kingdom	1092
Italy	159		

Panel B: Variables

Quintile	SIZE	BM	OP	INV	MOM
Low CO	798	0.78	0.83	0.22	-0.19
2	1267	0.75	0.83	0.19	-0.05
3	1430	0.75	0.86	0.18	0.08
4	1434	0.75	0.85	0.17	0.22
High CO	937	0.79	0.88	0.18	0.49

This table presents summary statistics for the countries included in the European sample and the variables used in this study. Panel A reports the average number of firms per month in each country over the sample period from July 1990 to June 2018. Panel B reports the quintiles sorted on the continuing overreaction measure. Firm size (SZ) is market equity (stock price multiplied by the number of shares outstanding) as of June of each year in million U.S. dollars. Book-to-market (BM) is the ratio of book equity to market equity at the fiscal year-end. Operating profitability (OP) is revenues minus cost of goods sold and interest expense, all divided by book equity. Investment (INV) is the annual change in total assets divided by total assets. Momentum (MOM) is the cumulative prior six-month stock return, skipping the most recent month.

Panel B of Table 1 summarizes the distributional statistic for the variables used in this study. A typical firm in the high (low) CO quintile of our European sample has a size of 937 (798) and a book-to-market ratio of 0.79 (0.78). Naturally, the momentum factor is much stronger (0.49) in the high quintile than in the low one (-0.19).

4.3 The CO-return relation

In this section, we test Hypothesis 1 that firms with a strong CO measure have higher subsequent stock returns than firms with a weak CO measure, culminating in the existence of a positive continuing overreaction–return relation. To examine how European stock returns vary with different levels of CO measure, we begin our analysis at the portfolio level. Specifically, at the end of each month, we form quintile portfolios by allocating stocks in ascending order to five groups based on their continuing overreaction measure from the previous month. Accordingly, a firm is assigned to the high (low) quintile portfolio if its CO measure is in the top (bottom) 20 per cent of the CO measures. Monthly returns are calculated for different holding periods from one up to 12 months after portfolio formation, portfolios are rebalanced each month.

Table 4.2 Continuing overreaction portfolios

Quintiles	1 Month	1st Year	2nd Year	3rd Year
Low CO	0.09	0.32	0.71	0.79
2	0.40	0.55	0.77	0.84
3	0.60	0.72	0.79	0.84
4	0.96	0.86	0.80	0.80
High CO	1.36	1.06	0.73	0.71
High - Low	1.27	0.74	0.02	-0.08
	(9.37)	(7.37)	(0.23)	(-1.00)

This table presents average monthly raw returns in percent for quintile portfolios sorted on continuing overreaction measure. The portfolios are formed every month by allocating stocks in ascending order to five groups based on their continuing overreaction measure from the previous month. The last row (High-Low) provides the average spread return between firms with high and low continuing overreaction measures. The t-statistic is given in parentheses.

Table 2 shows average monthly raw returns sorted on the continuing overreaction measure. The last row (High-Low) reports the spread return between firms with high and low continuing overreaction measures for testing whether the return difference is significantly different from zero. We observe that the portfolio returns ascend monotonically from firms with low CO to firms with high CO. For a one month holding period the H-L spread is statistically highly significant and amounts to 1.27 per cent per month (t-statistic 9.37). Similar to the well-known momentum effect, we observe significant H-L returns for a holding period of up to 12 months with 0.74 per cent per month (t-statistic 7.37). While momentum suffers from significant reversal after a one-year holding period, the portfolio formation on continuing overreaction displays no significant reversal even for a holding period of up to 36 months after portfolio formation.[36] It is notable that the High CO portfolio has significant positive returns for all observed holding

[36] For the reversal effect see e.g. Jegadeesh & Titman (1993).

periods. This is in sharp contrast to a standard momentum approach where the long side normally turns negative at the latest after a one-year holding period. These findings are mainly in line with Byun et al. (2016) who could not find return reversal within the U.S. equity market either.

Table 4.3 Robustness of CO measure

High - Low	1 Month	1st Year	2nd Year	3rd Year
(1)	1.24	0.64	-0.28	-0.39
Earlier	(5.40)	(3.89)	(-2.06)	(-3.09)
(2)	1.30	0.83	0.32	0.23
Later	(9.00)	(7.36)	(3.28)	(2.46)
(3)	1.52	0.84	0.08	-0.11
Small	(11.74)	(9.01)	(0.88)	(-1.16)
(4)	1.11	0.66	0.02	-0.08
Large	(6.81)	(5.42)	(0.16)	(-0.93)

This table presents average monthly raw returns in percent and associated t-statistics (in parentheses) sorted on the continuing overreaction measure. For clarity we only show the High-Low average return spread here. The earlier and later half samples cover July 1990 to June 2004 and July 2004 to June 2018, respectively. The small (large) sub-sample consists of the bottom (top) 50% of firms in each country in terms of market equity, measured as of June of each year.

Hitherto the results support our first hypothesis that there exists a positive relation between continuing overreaction and subsequent stock returns. To further examine the robustness of our European sample across time and firm size, we repeat our portfolio level analysis between two different sub-periods as well as small and large firms. The corresponding results are presented in Table 3; for reasons of simplicity we only display the High-Low portfolio returns.

Row (1) and (2) report sub-period results. The earlier sub-period runs from July 1990 to June 2004 (168 months), while the later sub-period is from July 2004 to June 2018 (168 months). The return premium of firms with high CO measures was present in the earlier subsample and is even stronger in the more recent sub-period. Interestingly, while in the earlier subsample the reversal was also present for the second and third year after portfolio formation, the subsample from 2004 to 2018 also displays a slightly significant positive return relation for longer holding periods, monthly 0.32 per cent (t-statistic 3.28) for the second year and still 0.23 per cent (t-statistic 2.46) in the third year.

A further cause for concern for anomalous return patterns is their pervasiveness across size. To address this question, rows (3) and (4) present size-segmented subsample results. The small (large) subsample consists of the bottom (top) 50% of firms in each county in terms of market equity, measured as of June of each year. As is the case for most other anomalies, the observed return effect is stronger among smaller firms, but it is not limited to them and is also significantly present among the largest and economically most important firms in European equity markets. We do not find that any of the sub-samples has a significant reversal for longer holding periods.

Table 4.4 Time series regressions

Panel A: CAPM

High - Low	1 Month	1st Year	2nd Year	3rd Year
Alpha	1.35	0.77	0.02	-0.10
	(9.27)	(6.23)	(0.23)	(-1.00)
Beta	-0.15	-0.07	0.00	0.03
	(-2.56)	(-1.52)	(-0.11)	(1.04)

Panel B: Carhart 4 Factor

High - Low	1 Month	1st Year	2nd Year	3rd Year
Alpha	1.13	0.64	0.08	0.01
	(10.59)	(7.23)	(0.89)	(0.08)
Beta	-0.06	-0.02	-0.04	-0.03
	(-1.70)	(-1.14)	(-1.14)	(-1.02)
SMB	0.00	-0.11	-0.18	-0.21
	(0.02)	(-3.28)	(-5.43)	(-5.90)
HML	-0.12	-0.16	-0.26	-0.15
	(-1.44)	(-3.40)	(-6.37)	(-4.11)
WML	0.32	0.22	0.04	-0.07
	(12.62)	(11.42)	(1.32)	(-3.87)

This table presents results from time-series regressions to explain the return premiums on the High – Low CO strategy. High - Low buy firms with a CO measure within the top 20 % of all firms and a sell firms with a CO measure in the bottom 20 %. The table shows the average monthly (first column) and yearly premiums in percent, the alpha estimates, and the factor sensitives depending on the CAPM (Panel A) and the Carhart four-factor model (Panel B). The t-statistic is given in parentheses.

To conclude this chapter, we finally test whether the abnormal returns are just a compensation of risk. Table 4 shows estimates based on the CAPM, the three-factor model and the Carhart four-factor model regressions over the full sample period.[37] Panel A of Table 4 shows the CAPM results; we find economically substantial and statistically significant alpha estimates in our European sample. Once again, the return premium among firms with high CO is measurable during the first year after portfolio formation, but no reversal appears in the long term.

Controlling additionally for firm size and value/growth characteristics, Panel B of Table 4 shows results for the three-factor model (Fama French 1993). Interestingly, the alpha increases slightly for all holding periods compared to the CAPM alphas. From the negative loadings on the SMB and HML factors, we learn that the High-Low portfolio is nested within large stocks with growth characteristics. Panel C of Table 4 shows results for the four-factor model (Carhart 1997) where we additionally add the Momentum factor to the time-series regression. As a result of the high correlation between the CO measure and the momentum factor the alphas in the four-factor model diminish within the first year.[38] However, we still find statistically and economically significant returns in up to twelve months holding periods. While in the U.S. the four-factor alphas shrink down to about a half compared to the three-factor ones, in our European sample the alpha reduces only 24bps from 0.88 per cent per month to 0.64 per cent with a strong t-statistic of 7.23.

All in all, the results in this section strongly support Hypothesis 1. Similar to the remarkable findings of Byun et al. (2016) on the U.S. stock market, we observe a powerful positive relation between the CO measure and subsequent stock returns on the European stock market as well.

[37] For simplicity we only show the high-low portfolio results.
[38] We have also redone the calculations with the three-factor model. As results stay very similar for clarity we only present results for the CAPM and the four-factor model here.

4.4 Return Effects of High and Low CO Measures with Controls

Portfolio sorts represent a very useful approach for investigating how average returns vary with different levels of CO measures. However, the portfolio-level analysis suffers from the lack of lost individual stock information through aggregation. Furthermore, showing that a positive return premium exists does not rule out the possibility that the identified return effect is just a manifestation of already known determinants of the cross section of average stock returns.

To test Hypothesis 2, we therefore examine the return effects at the individual firm level using Fama and MacBeth (1973) methodology, in this section. They provide a test setting that easily allows for multiple control variables. To address this issue, we estimate a monthly firm level cross-sectional regression of the firm's future return on common firm characteristics that all predate the dependent variable.

In particular, the future return of firm i in month t is regressed on two binary indicator variables, denoted High and Low, in conjunction with common controls that are all available before the month in which the return measurement begins:

$$r_{i,t} = a_{0,t} + a_{1,t}\mathrm{High}_{i,t} + a_{2,t}\mathrm{Low}_{i,t} + a_{3,t}\ln(\mathrm{SZ}_{i,t}) + a_{4,t}\mathrm{BM}_{i,t} + a_{5,t}\mathrm{OP}_{i,t} + a_{6,t}\mathrm{INV}_{i,t} + \text{Country Dummies}_{i,t} + e_{i,t}. \quad (3)$$

To correct for the holding period overlap in the statistical inference (Jegadeesh and Titman 1993) we apply Newey and West (1987) adjusted t statistics in all subsequent regressions.

The high (low) CO indicator is equal to one if the firm's continuing overreaction measure is in the top (bottom) 20 per cent of all CO measures, and zero otherwise. Taking into account the most recent developments in asset pricing, the set of common firm characteristics includes firm size, book-to market, momentum, operating profitability, and investment, that all serve as common control variables in the later cross-sectional return analyzes (Fama and French 2015). All explanatory variables are updated each June, except for momentum, which is updated monthly. Furthermore, to control for possible country effects, we include country dummies in all our regressions. Thus, the average coefficient estimate measures the within-country effects, that is, the variables' return-predictive ability in a typical country of the sample.

Table 4.5 Cross-sectional regressions

Panel A: Without Controls

	1 Month	1st Year	2nd Year	3rd Year
High CO	0.67	4.97	-0.34	-1.18
	(6.51)	(4.39)	(-0.37)	(-1.37)
Low CO	-0.53	-4.4	-0.25	-0.12
	(-6.62)	(-5.59)	(-0.31)	(-0.18)
R^2	0.03	0.04	0.03	0.03
High-Low	1.21	9.37	-0.09	-1.06
	(7.80)	(5.83)	(-0.06)	(-0.74)

Panel B: With Common Controls

	1 Month	1st Year	2nd Year	3rd Year
High CO	0.15	2.6	0.57	-0.38
	(2.67)	(3.97)	(0.99)	(-0.96)
Low CO	-0.17	-2.59	-0.66	-0.34
	(-2.69)	(-4.67)	(-1.12)	(-0.66)
SZ	0.06	0.02	0.16	0.16
	(2.09)	(0.04)	(0.40)	(0.40)
BM	0.28	3.41	3.35	2.89
	(2.83)	(1.97)	(1.93)	(1.91)
OP	0.1	1.68	1.69	1.6
	(3.90)	(4.14)	(3.88)	(4.02)
INV	-0.38	-3.07	-2.77	-1.85
	(-5.50)	(-2.41)	(-2.56)	(-2.03)
MOM	1.15	5.18	-2.48	-1.45
	(3.50)	(1.68)	(-1.01)	(-0.65)
R^2	0.05	0.06	0.05	0.05
High-Low	0.33	5.19	1.23	-0.04
	(3.06)	(5.39)	(1.42)	(-0.06)

This table presents average coefficient estimates and associated Newey-West adjusted *t*-statistics (in parentheses) from monthly firm-level cross-sectional regressions. The dependent variable is the firm's future one month, first-year, second-year or third-year return after the CO calculation. High (Low) CO is a binary indicator variable that takes the value of one if a firm's CO measure is in the top (bottom) 20 % of all firms and zero otherwise. The independent variables are firm size (SZ), book-to-market (BM), operating profitability (OP), investment (INV), and momentum (MOM). All regressions include country dummies. In the regressions, SZ and BM are measured in natural logs. R^2 is adjusted for degrees of freedom. The last row provides the average return premium in percent based on the difference between the high and low coefficient estimates. Panel A reports results for the high and low coefficient estimates without controls. Panel B contains additional results for the full set of independent controls.

Table 5 shows average coefficient estimates from the outlined firm-level cross-sectional regressions of overlapping yearly returns without controls to assess the high-low return behavior. The last row of each panel reports the difference between firms with high and low measures of continuing overreaction. As expected, we find an economically strong and statistically significant premium in the first year of 9.37, which is equally driven by the high CO indicator (4.97 %) and a negative low CO indicator (-4.40 %). The high-low premium is only significant in the first year after portfolio formation and becomes insignificant thereafter.

Panel B of Table 5 includes the common controls as a further robustness test. The premium shrinks less than 1 per cent to 8.52 % for a one year holding period after portfolio formation and is still strongly significant (t-statistic 5.49). While size and book-to-market are insignificant, operating profitability loads positive and the investment factor significantly negative on the return premium.

To finally conclude whether momentum drives out the return premium of the continuing overreaction measure we include a momentum factor to the regression in Panel C of Table 5. While the momentum factor leads towards significance in the first year (t-statistic 1.68), it turns negative in the second year. The CO premium stays significant positive at 5.19 for the first year and still becomes insignificant thereafter.

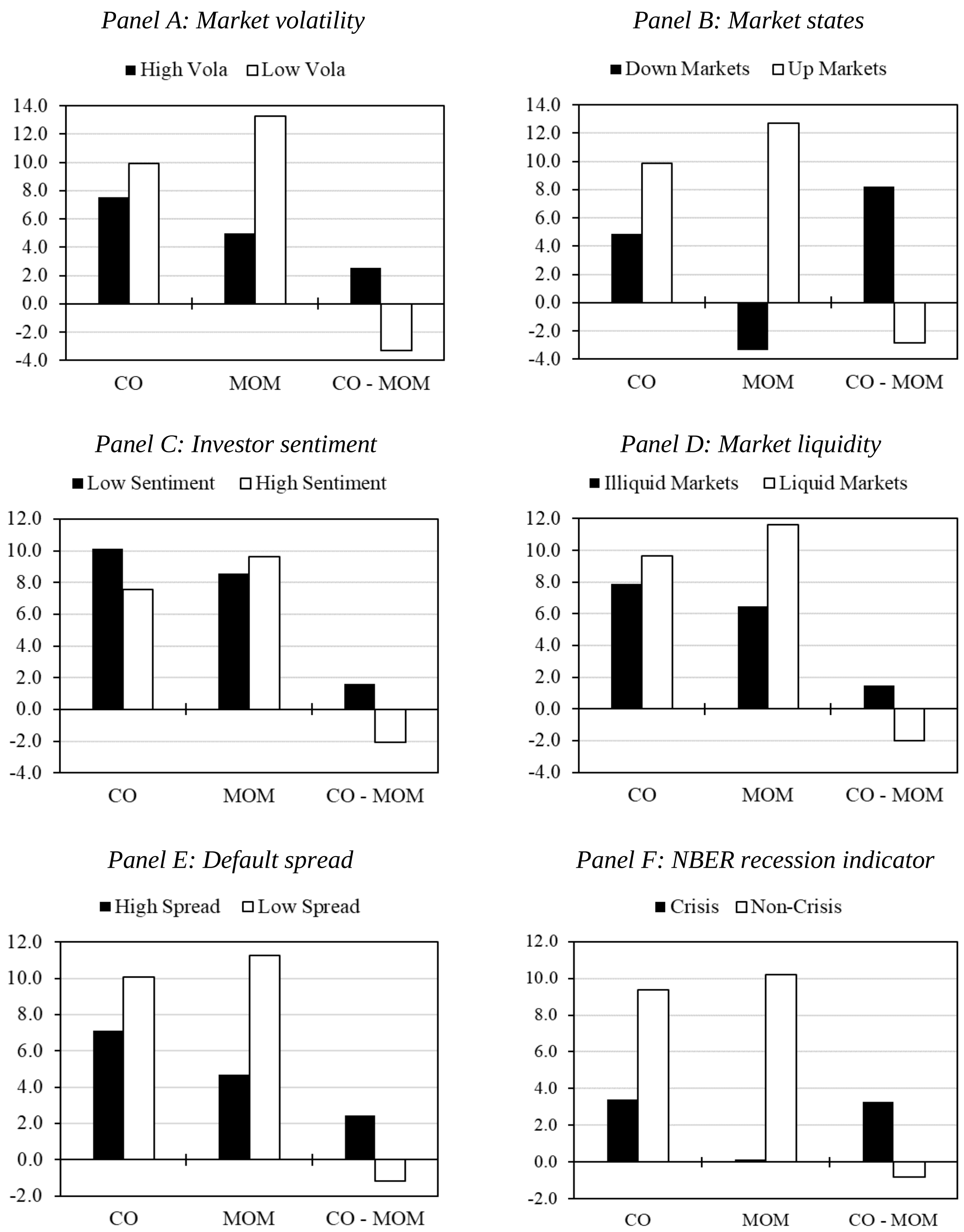
In summary, the results in this section strongly support our Hypothesis 2. Similar to the results of prior U.S. studies, we observe an economically strong and statistically significant CO premium, that could not be explained by established cross-sectional determinates. Interestingly, even if we add a momentum factor, the CO premium stays significant.

4.5 CO measures within different business conditions

In this section, we test Hypothesis H3 that the return premium between firms with high measures of CO and firms with low CO is also present within different business conditions. It is well established that momentum profits vary within different business conditions. Chordia and Shivakumar (2002) were among the first to show that momentum performs well during expanding periods while the momentum premium is smaller within recessive periods, based on the NBER recession indicator. Further studies expand these findings with various measures of optimistic/expanding economy states versus contracting/pessimistic economy states (Jegadeesh and Titman 2011). Hereinafter we examine whether the novel continuing overreaction measure conforms to the same return pattern as with a standard momentum approach. To address this question, we estimate monthly firm-level cross-sectional regressions based on Equation (3) for two different specifications, i.e., negative versus positive specifications that depend on the underlying state of the economy. We use six different proxies to measure the positive/negative economic states. Namely: market volatility, market states, investor sentiment, market liquidity, default spread, and the NBER recession indicator. While market volatility as well as market states are based on European data, due to missing cross-country proxies, the remaining four measures are based on US data. Baker, Wurgler and Yuan (2012) demonstrate that sentiment around the globe is predominantly driven by the US sentiment and that this can therefore serve as a proxy for European sentiment as well. Moreover, the USA as the world's largest and most important equity market take up a leading role for international markets as documented by Rapach, Strauss and Zhou (2013).

The six different proxies to measure the state of the economy are defined in the following way. Following Baker and Wurgler (2006), market volatility is the annual standard deviation of the value-weighted European market portfolio returns over the prior 12 months, skipping the most recent month. Market state is calculated using the cumulative return on the value-weighted European market portfolio over the 36 months ahead of the calculation point of the continuing overreaction measure (Cooper, Gutierrez, and Hameed 2004). We use the well-known Baker and Wurgler (2006) sentiment index, that uses monthly US data, to capture investor sentiment. Market liquidity is measured using the noise index of Hu, Pan and Wang (2013) that uses the aggregate noise in the prices of US Treasury bonds, thus the deviation between market and model-implied yields. We use the level of noise in the US Treasury bond market as a proxy for market-wide liquidity due to the fact that this market is one of the most active and liquid markets in the world and one with the highest credit quality. Default spread is the monthly difference between a 10-year US corporate bond index and 10-year US Treasury bonds, as applied by Fama and French (1993). To separate crisis from non-crisis periods over the sample period, we use the NBER recession indicator for the USA. We calculate the median of market volatility, investor sentiment, market liquidity and default spread to separate between optimistic and pessimistic values for those measures, while positive (negative) 36-month returns of the market indicate up (down) market states.

Figure 4.1 Premiums conditional upon business conditions



This figure illustrates the average return premiums associated with the continuing overreaction measure (CO), a standard momentum strategy (MOM) and the difference of both strategies (CO – MOM) in percent per year during contracting/pessimistic business conditions (black bars) and expanding/optimistic business conditions (clear bars), as measured by six different economic state proxies (Panels A to F).

Figure 1 illustrates the average return premiums related with continuing overreaction and a standard momentum approach; the last bars provide the difference between the CO and momentum measure. The black bars illustrate pessimistic (contracting) business conditions while the clear bars display the optimistic (expanding) business conditions, as calculated by the six proxies for the state of the economy (Panel A to F). The premiums are the results from the differences between the high and low (long and short) coefficient estimates from the outlined firm-level cross-sectional regression setting. As before, we include common controls and country dummies in every single regression.

Notwithstanding the economic state proxy, both approaches gain significantly positive return premiums during optimistic periods. Across all proxies, the average CO profit amounts to 9.40 % per year while a standard momentum approach gains 11.44 % per year, as a consequence, the difference between the CO and momentum approach during positive business conditions is negative (-2.04 % per annum). The strong momentum premium during positive periods, as already documented by previous literature, leads to the observed return pattern and the superiority of the momentum strategy here. Chordia and Shivakumar (2002) find a significant positive return premium only during expanding periods, as well as Antoniou, Doukas and Subrahmanyam (2013) who show that momentum profits are high during up markets and insignificant low in down markets, following the approach of Baker and Wurgler (2006) for sentiment calculations.

As a natural consequence, regardless of the applied economic state proxy, the average return premium during negative periods is significantly stronger among the novel continuing overreaction measure. The average CO premium amounts to 6.78 % per annum while the momentum premium gains only 3.58 %, which leads to a positive difference between the two approaches of 3.20 % per annum. Especially worth mentioning is the superiority of the CO measure regarding the proxies for crisis/non-crisis (NBER recession indicator) and up/down markets. During these pessimistic periods the momentum premium is near zero (crisis) or even strongly negative (down markets), while the CO measure gains significantly positive return premiums irrespective of the applied economic state.

In summary, on the one hand, these empirical results corroborate the findings by prior literature that the momentum premium is particularly strong during expanding/optimistic periods and very weak during contracting/pessimistic periods. On the other hand, these results clearly point out the superiority of the CO measure over a one year holding period in comparison to a standard momentum approach, displayed in the continuity especially during contracting/pessimistic periods.

4.6 Conclusion

In this paper, we study the U.S. findings of Byun et al. (2016) that a continuing overreaction measure can predict future stock returns in the broad cross section of European firms drawn from 15 developed equity markets over the sample period from 1990 to 2018. The measure is calculated by taking the weighted signed volume as well as past returns into account. We provide strongly supportive out-of-sample evidence on the previous findings on the U.S. stock market.

As in the United States we find a significantly positive relation between firms' continuing overreaction measure and the subsequent stock return. The outperformance of firms with high measures of continuing overreaction over low CO measures is not captured by established cross-sectional return determinants. The observed premium is robust to common controls based on firm size, book-to-market and momentum as well as to novel controls like profitability and investment. In addition, the premium is also present within different business conditions, we use market volatility, market states, investor sentiment, market liquidity, default spread, and the NBER recession indicator. In depth, the novel CO measure earns a significantly positive return premium over a holding period of one year that does not suffer from reversal as a standard momentum approach does in the subsequent years. Companies with high CO measures gain abnormal returns over an observed holding period of up to three years.

Given the similarity between our European findings and the prior US evidence, it is unlikely that the superior predictive power of CO measure is sample-specific. Indeed, our results suggest that the continuing overreaction measure is a superior applicable measure even in Europe.

Chapter 5

Dissecting value-growth strategies conditioned on expectation errors

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Abstract We examine the previously documented effect between a firm's FSCORE and book-to-market ratio proposed by Piotroski and So (2012) and analyze their expectation errors hypothesis from a present value perspective. We find a strong value premium, which is concentrated among firms where book-to-market implied expectations are incongruent with underlying fundamental strength. Using the decomposition of variation in book-to-market ratios motivated by Cohen et al. (2003), we show that the observed effect between a firm's FSCORE and book-to-market ratio is attributable to mispricing as the variation is mostly due to variation in expected returns rather than variation in expected profitability.

Keywords Value; Mispricing; International markets; Decomposition; Behavioral finance

5.1 Introduction

The empirical observation that firms with high book-to-market (BM) ratios outperform firms with low BM ratios – defined as the value premium – dates almost 30 years back to the seminal paper of Fama and French (1992). Since then, the value premium has been one of the most examined return anomalies in asset pricing history. Despite this enormous effort, the explanation for the existence of the value premium is still an ongoing debate. Contrary to the risk-based explanation motivated by Fama and French (1992), a growing strand of literature, starting with Lakonishok et al. (1994), provides evidence that the value premium is the result of behavioral biases of market participants. A prominent behavioral explanation is that high (low) values on BM signal pessimistic (optimistic) expectations concerning a firm's future earnings performance, reflecting investor's tendencies to over-react to past fundamentals. These biased expectations systematically reverse in response to new information, giving rise to positive value-growth returns (see, La Porta et al. [1997]; Griffin and Lemmon [2002]; Ali et al. [2003], among others).

Building upon the findings that the value premium is attributable to systematic errors in expectation and subsequent price correction, Piotroski and So (2012) propose a seminal investment strategy approach that combines firms' BM ratio with Piotroski's (2000) accounting-based measure FSCORE. The FSCORE serves as an indicator of a firm's fundamental strength, where strong fundamentals are expressed by high values on FSCORE and weak fundamentals by low values on FSCORE. Defining investors' systematic errors in expectation as *market expectation errors*, revisions of these expectation errors are shown to be ex ante existent when expectations implied by the BM ratio are incongruent with the actual fundamental strength of the firm. Analyzing the US market, Piotroski and So (2012) document that the value premium is most pronounced among firms with ex ante identifiable expectation errors and absent among firms without these expectation errors. Since then, the application of the FSCORE to proxy for a firm's underlying fundamental strength has become increasingly popular. For example, Ng and Shen (2016) and Walkshäusl (2017) provide extensive out-of-sample evidence in favor of the results of Piotroski and So (2012) for international markets, suggesting that investor's expectation errors indeed explain the value premium. Furthermore, Tikkanen and Äijö (2018) show that a similar effect can be observed when the FSCORE is combined with other fundamental valuation ratios. Besides beneficial interaction effects, Hyde (2018), Ng and Shen (2019), and Walkshäusl

(2020) provide evidence that the FSCORE itself is informative about expected returns. Finally, a FSCORE-based investment strategy is even able to explain priced-based anomalies like momentum among US (Ahmed and Safdar 2018) and European stocks (Walkshäusl 2019).

Despite the enormous evidence it is questionable if the observed interaction effect between FSCORE and the BM ratio is the result of mispricing or just the realization of expected profitability. Specifically, Cohen et al. (2003) propose a present value model, which allows to decompose a firm's current BM ratios into the following components: expected stock return, expected profitability, and future BM ratio. Building upon the clean-surplus accounting relations, they derive an approximation:

$$\mathrm{bm}_{t-1} = \sum_{j=1}^{N} \rho^{j} r_{t+j} - \sum_{j=1}^{N} \rho^{j} e_{t+j} + \rho^{N+1} \widetilde{\mathrm{bm}}_{t+N} \tag{1}$$

where bm, r, e, are the log BM ratio, log stock return, and the log clean-surplus accounting profitability, while ρ represents a positive discounting parameter close to one.[39] Cohen et al. (2003) use the BM decomposition in equation (1) to reveal that most of the cross-sectional variation in BM ratios can be linked to differences in expected profitability, proxied by the clean-surplus profitability measure, suggesting that firm-level stock returns are mainly driven by changes in cash-flow expectations, not by changes in expected returns.

Our motivation for this paper is threefold. First, we provide fresh out-of-sample evidence for the previously found connection between the FSCORE and the value premium. Second, in line with the present value model proposed by Cohen et al. (2003), we decompose the BM ratios of value and growth firms to analyze the value premium from a cashflow-driven perspective. Third, we extend the decomposition results by examining how the FSCORE affects value-growth portfolios using the present value model. We hypothesize that the value premium should be absent among stocks without market expectation errors, as their current market valuations are more likely driven by rational cash-flow expectations and information on expected profitability is incorporated into market prices, while, on the other hand, existent market expectation errors might lead to the realization of positive value-growth returns, as their BM ratios may not only contain information about cash-flow expectations but also about expected

[39] A detailed derivation of this expression is provided in the Appendix.

stock returns due to price corrections arising from the reversal of these expectation errors. Showing that the cross-sectional variation in BM ratio is not solely linked to expected profitability, but also to variation in expected return when expectation implied by BM ratio is incongruent with fundamental strength, would provide supportive evidence to a mispricing-based explanation which is central to our paper.

The remainder of the paper is organized as follows. The next section describes the data. The subsequent sections discuss the outlined methodology and present the empirical results. The final section concludes.

5.2 Data and Variables

Motivated by the well-known stock market benchmark MSCI EAFE (Europe, Australia, and the Far East), our sample comprises firms from 20 developed non-US equity markets, which represents an adequate dataset to proxy for foreign stock market performance outside of North America. We collect monthly total return data on common stocks from Datastream and firm-level accounting information from Worldscope. In order to make sure that our empirical analysis does not suffer from a lookahead bias, we employ a six month time lag and match the latest accounting information for the fiscal year ending of the previous year with stock returns from July of the current year to June of the subsequent year throughout the paper. All data are denominated in US dollars. In line with Ang et al. (2009), we exclude 5% of firms with the lowest market value of equity in each country per year to reduce the possibility that our results are biased by tiny and illiquid stocks. Additionally, as in Fama and French (1992), we treat firm-year observations with negative book equity as missing values and exclude financial firms with Standard Industrial Classification (SIC) codes between 6000 and 6999 from the sample. Finally, we require that all accounting information necessary to calculate the FSCORE is available for the fiscal year ending in the previous year to be included in the sample. Our data sample covers the period from July 1990 to June 2018 (henceforth 1990-2018) and consists on average of 5162 firms per year. Panel A of Table I contains the summary information regarding the distribution of firms across countries.

Table 5.1 Summary statistics

Panel A: Sample countries

Country	Firms
Australia	506
Austria	30
Belgium	43
Denmark	72
Finland	69
France	330
Germany	258
Hong Kong	405
Ireland	29
Italy	127
Japan	1,645
Netherlands	88
New Zealand	48
Norway	84
Portugal	26
Singapore	258
Spain	59
Sweden	158
Switzerland	109
United Kingdom	818

Panel B: Variables

	SZ	BM	FSCORE	OP	INV
Mean	1,352	0.91	5.60	0.75	0.10
25th percentile	48	0.42	4.55	0.28	-0.04
50th percentile	163	0.73	5.69	0.54	0.05
75th percentile	681	1.20	6.79	0.94	0.16

This table shows summary statistics for the countries covered in the international (EAFE) sample and the variables used in the study. Panel A reports the average amount of firms per month within a country over the sample period from July 1990 to June 2018. Panel B reports the distribution of the variables. The statistics include mean, 25th percentile, median, and 75th percentile. Firm size (SZ) is measured as market value of equity (stock price multiplied by the number of shares outstanding) as of the end of June of each year in million U.S. dollars. Book-to-market (BM) measures the ratio of a firm’s book equity to market equity at the fiscal year-end. FSCORE is an aggregate accounting-based measure of the firm’s fundamental strength. Operating profitability (OP) is revenues minus cost of goods sold and interest expense, all divided by book equity. Investment (INV) is the annual change in total assets scaled by total assets.

We define a firm's size as its market equity (calculated by multiplying the stock price by total outstanding shares) measured as of June each year in million US dollars. BM is a firm's book equity relative to its market equity at the fiscal year-end. Profitability (PRO) is revenues minus operating expenses (cost of goods sold and interest expense) scaled by book equity (Fama and French 2015). Investment (INV) is the annual change in total assets scaled by the prior year's total assets. Following Piotroski (2000), the FSCORE indicator comprises nine individual binary signals measuring various aspects of a firm's fundamental strength. A signal is equal to one if the underlying condition is favorable and zero otherwise. The nine signals are defined as follows. (1) return-on-assets (net income before extraordinary items scaled by lagged total assets) is positive, (2) annual change in return-on-assets is positive, (3) operating cash flow scaled by lagged total assets is positive, (4) operating cash flow is greater than net income before extraordinary items, (5) the annual change in long-term debt scaled by average total assets is negative, (6) the annual change of a firm's current ratio (current assets to current liabilities) is positive, (7) a firm did not issue equity, (8) the annual change of a firm's gross margin (sales minus cost of goods sold scaled by sales) is positive, and (9) the annual change in a firm's asset turnover (total sales scaled by lagged total assets) is positive.

Panel B of Table I summarizes the distributional statistics of the variables outlined before over the 1990 to 2018 sample period. A typical firm in our international sample has a size of $1,352 million in terms of market equity, an average relative valuation based on book-to-market of 0.91, and an average FSCORE of around five signaling a medium fundamental strength.

5.3 Return behavior of value-growth strategies conditioned on expectation errors

We begin our analysis at the portfolio level using univariate and bivariate sorts. Applying univariate portfolio sorts based on the BM ratio and FSCORE respectively allows us to assess return premia associated with value and a firm's fundamental strength in international equity markets on a standalone basis. Then, using bivariate portfolio sorts based on the BM ratio and FSCORE, value-growth returns are evaluated upon the degree to which implied expectations are consistent with underlying fundamentals. Portfolios are formed annually at the end of June of the current year by ranking stocks based on BM, FSCORE, and both variables from the fiscal year ending in the previous year. A firm is designated as a growth, neutral, or value stock if its BM is in the bottom 30th percentile, between the 30th percentile and 70th percentile, or in the top 70th percentile. A firm is designated as a weak, medium, or strong stock if its FSCORE is below three, between four and six, or above six. We track the subsequent equal-weighted monthly returns for each portfolio from July of the current year to June of the subsequent.

Panel A of Table II shows average monthly equal-weighted returns and firm characteristics for the single portfolio sorts. When portfolios are sorted by BM or FSCORE respectively, we find statistically significant and economically large return spreads in international equity markets. Value firms with high BM ratios outperform growth firms with low BM ratios by 0.58% per month over the whole sample period. Fundamentally strong firms with a high FSCORE generate a significant return spread of 0.64% per month over fundamentally weak firms with a low FSCORE. In line with prior research, value firms display on average a smaller market capitalization, lower profitability and lower investments compared to growth firms (e.g. Fama and French 2015). Considering the portfolio sorts on the FSCORE characteristic, fundamentally strong firms are larger in terms of market equity and display higher profitability than fundamentally weak firms, whereas investment does not differ meaningfully within the sorts. However, both portfolio sorts indicate that there is no meaningful relationship between the BM and FSCORE characteristic.

Table 5.2 Portfolio sorts

Portfolio	Return	*(t-stat)*	Characteristics					
			BM	SZ	OP	INV	FSCORE	Firms
Panel A: Single Sorts								
Book-to-Market								
Growth	0.62		0.29	2,026	1.12	0.20	5.46	1,549
Neutral	0.83		0.74	1,354	0.70	0.11	5.70	2,065
Value	1.20		1.76	380	0.48	0.04	5.60	1,549
V-G	0.58	*(4.27)*						
FSCORE								
Weak	0.47		0.95	576	0.60	0.10	2.54	646
Medium	0.84		0.91	1,331	0.77	0.12	5.15	2,856
Strong	1.10		0.91	1,360	0.82	0.11	7.47	1,660
S-W	0.64	*(3.99)*						

Portfolio	Return	*(t-stat)*	Characteristics					
			BM	SZ	OP	INV	FSCORE	Firms
Panel B: Double Sorts								
Growth x Weak	0.18		0.26	723	0.98	0.18	2.51	236
Growth x Medium	0.62		0.29	2,109	1.16	0.21	5.13	870
Growth x Strong	0.84		0.31	2,452	1.19	0.18	7.44	443
Value x Weak	0.77		1.90	257	0.34	-0.01	2.56	193
Value x Medium	1.11		1.77	421	0.48	0.04	5.15	846
Value x Strong	1.36		1.70	336	0.55	0.05	7.49	510
No Expectation Errors	-0.07	(-0.40)						
Potential Expectation Errors	0.49	(3.72)						
Existent Expectation Errors	1.19	(5.11)						

The table shows average monthly equal-weighted returns in percent. In Panel A, we sort stocks based on BM or FSCORE. In Panel B, we sort stocks based on BM and FSCORE. For both panels, the portfolio formation is based on the relevant variable(s) at the ending of the fiscal year in the preceding calendar year. A firm is characterized as Growth, Neutral, or Value if its BM ratio is below the 30th percentile, between the 30th and 70th percentiles, or above the 70th percentile, respectively. A firm is characterized as Weak, Medium, or Strong if its FSCORE is less than or equal to three, between four to seven, or greater than or equal to seven, respectively. The standard value strategy (V-G) takes a long position in value firms and a short position in growth firms. The standard FSCORE strategy (S-W) takes a long position in fundamentally strong firms and a short position in fundamentally weak firms. A stock is assigned to the *no expectation errors* portfolio if its BM is congruent with the fundamental strength (Growth × Strong or Value × Weak). A stock is assigned to the *existent expectation errors* portfolio if its BM is incongruent with the fundamental strength (Growth × Weak or Value × Strong). Growth and value stocks with medium FSCORE are assigned to the *potential expectation errors* portfolio. Newey and West (1987) adjusted t-statistics for the return premia are given in parentheses. The table also reports average firm characteristics as well as the average amount of firms observed per month.

To examine the impact of market expectation errors, we further study the interaction of BM with FSCORE using bivariate sorts. We follow Piotroski and So (2012) and build value-growth portfolios alongside different dimensions of expectation errors. Firms with high BM ratios are generally expected to have weak fundamentals, while firms with low BM ratios are expected to have strong fundamentals. Therefore, a strategy that takes a long position in value firms with weak fundamentals and a short position in growth firms with strong fundamentals is not exposed to expectation errors. Contrary to that, a strategy that takes a long position in value stocks with strong fundamentals and a short position in growth stocks with weak fundamentals is exposed to expectation errors. In between, value firms with medium fundamental strength and growth firms with medium fundamental strength are potentially exposed to expectation errors.

Panel B of Table II reports average monthly equal-weighted returns for bivariate sorts based on BM and FSCORE and the return spreads for the three different value-growth portfolios. We observe that bivariate FSCORE sorts induce significant return variation within value firms as well as growth firms. The return spreads between firms with value and weak fundamentals are significantly different from zero regardless of the BM categorization. Likewise, value firms significantly outperform growth firms after controlling for FSCORE. The results imply that the information about expected returns contained in the BM ratio and FSCORE is different. Turning to the results for the three value-growth portfolios with different degrees of implied expectation errors, we observe that the combination of BM and FSCORE has a major influence on the value-growth relationship in international equity markets. If a firm's fundamental strength is congruent with its BM implied expectations, that is value firms that are expected to have weak fundamentals actually have a low FSCORE and growth firms that are expected to have strong fundamentals actually have a high FSCORE, the previously observed return spread between value-growth firms decreases from 0.58% to -0.07% per month and is no longer distinguishable from zero. Contrary to that, if we consider the value-growth strategy with existent expectation errors, the return spread even increases to a highly significant premium of 1.19% per month. In line with the expectation error hypothesis, the portfolio consisting of value and growth firms with a medium FSCORE, which implies that there exist potential expectation errors, generates a significantly positive return premium of 0.49% per month. To summarize our results, which are consistent with prior evidence for the US and Europe, the combination of BM and FSCORE allows one to ex ante identify value and growth firms with existent market expectation errors which enhances the returns compared to a traditional value-growth strategy in international equity markets by 0.61% per month.

As described above, there is considerable variation regarding the average firm characteristics induced by bivariate FSCORE sorts which ultimately raises the question whether the observed return effects are potentially biased by other well-known return determinants. It is conceivable that these firm characteristics could at least explain parts of the premium, and thus the identified FSCORE effect would no longer be pronounced on a risk-adjusted basis. To address this concern, we further study the interaction effects of BM and FSCORE in a cross-sectional setting at the individual firm-level using the methodology proposed by Fama and MacBeth (1973). In line with our motivation to decompose BM ratios, we are particularly interested how the BM ratios of the three value-growth portfolios displayed in Table II are priced in a cross-sectional setting. Therefore, we estimate the following cross-sectional regression within four restricted specifications:

$$r_{i,t} = a_{0,t} + a_{1,t}BM_{i,t} + a_{2,t}\ln\left(SZ_{i,t}\right) + a_{3,t}OP_{i,t} + a_{4,t}INV_{i,t} + Country\ Dummies_{i,t} + e_{i,t} \tag{2}$$

Based on the univariate BM sorts, specification (1) comprises all value and growth firms in our overall data sample. We further split up this sample based on a firms FSCORE categorization to create three subsamples with very similar distributional statistics regarding BM ratios but varying degrees of expectation errors which resemble the three value-growth strategies outlined in Table II. Specification (2) comprises value firms with weak fundamentals and growth firms with strong fundamentals. Accordingly, expectation errors due to the misalignment of BM implied fundamentals and actual fundamentals should not exist. Contrary to that, specification (4) is constructed on the premise to maximize expectation errors and therefore includes value firms with strong fundamentals and growth firms with weak fundamentals. In between, specification (3) captures all value and growth firms with medium fundamentals and contains potential expectation errors. The purpose of conducting these various cross-sectional regressions with independent samples is to demonstrate how firm characteristics are priced in the different value-growth strategies. Based on our observation in Table II, we also conduct difference-of-means tests on cross-sectional regression estimates to examine whether the observed return-variable relations differ across the subgroups. Following the most recent developments in asset pricing, the set of common firm characteristics includes firm size, BM, profitability, and investments (Fama and French 2015). To control for possible country effects, we include country dummies in all regression specifications. The explanatory variables are updated annually at the end of each June in the previous calendar year.

Table 5.3 Regressions of value-growth return differences on firm characteristics

	Regression estimates				Difference-of-means tests		
Specification	(1)	(2)	(3)	(4)	(4)-(2)	(4)-(3)	(3)-(2)
Sample	Value-Growth	No Expectation Errors	Potential Expectation Errors	Existent Expectation Errors			
BM	0.34	0.13	0.35	0.57	0.44	0.21	0.22
	(5.00)	*(1.32)*	*(5.42)*	*(5.13)*	*(3.16)*	*(2.40)*	*(2.81)*
SZ	-0.01	-0.02	-0.01	-0.08	-0.07	-0.07	0.01
	(-0.50)	*(-0.57)*	*(-0.44)*	*(-2.52)*	*(-2.25)*	*(-2.99)*	*(0.25)*
OP	0.07	0.08	0.05	0.10	0.02	0.05	-0.03
	(2.99)	*(2.63)*	*(1.97)*	*(2.35)*	*(0.42)*	*(1.36)*	*(-1.04)*
INV	-0.35	-0.40	-0.31	-0.50	-0.10	-0.19	0.08
	(-4.52)	*(-2.90)*	*(-3.39)*	*(-4.19)*	*(-0.62)*	*(-1.46)*	*(0.75)*
R^2	0.08	0.10	0.09	0.10			
Observations	3,098	636	1,716	746			

The table shows average coefficient estimates and their corresponding Newey-West adjusted t-statistics (in parentheses) from cross-sectional regressions. We report return differences for each value strategy, as well as difference-of-means tests on the average slopes between the strategies. All regressions are estimated monthly, using firm characteristics at the end of June to explain returns for July through to June of the subsequent year. The set of firm characteristics comprises book-to-market (BM), firm size (SZ), operating profitability (OP), investment (INV), and country dummies. The R^2 value is adjusted for degrees of freedom. The final row reports the average number of sample firms for each year. A stock is assigned to the *no expectation errors* portfolio if its BM is congruent with the fundamental strength (Growth × Strong or Value × Weak). A stock is assigned to the *existent expectation errors* portfolio if its BM is incongruent with the fundamental strength (Growth × Weak or Value × Strong). Growth and value stocks with medium FSCORE are assigned to the *potential expectation errors* portfolio.

We start by discussing specification (1) of Table III, which relates the conventional value-growth returns to firm characteristics. For the standard value strategy, all coefficient estimates are significant with the exception of firm size indicating that the majority of explanatory variables provides useful information about the cross-section of value-growth returns. Unsurprisingly, we find that returns are positively associated with BM and profitability, while they are negatively associated with corporate investments, which is consistent with recent international evidence (e.g. Fama and French 2012, 2017). In a second step, we examine the return behavior of value-growth strategies formed along market expectation errors. Specification (2) presents the results for the value-growth subsample which is not exposed to expectation errors, while specification (3) comprises the value-growth subsample which is potentially exposed. Finally, specification (4) shows the results for the value-growth subsample with existing expectation errors. First, we observe a strong relationship between the level of implied expectation errors and the value premium after controlling for common return determinants. The BM coefficient estimate in specification (2) is statistically indistinguishable from zero, which implies that even though the subgroup solely consists of firms categorized as value and growth firms that there exists no value premium if implied expectations are aligned with a firm's fundamental strength. In contrast to that, the BM coefficient estimate becomes positive and statistically significant for value and growth firms within the potential-mispricing and mispricing subsample, indicating that the existence of a value premium strongly relates to market expectation errors. Second, the difference-of-means tests in the last three columns of Table III show that the average book-to-market estimates within the three subgroups of value-growth firms are statistically different from each other, while the return premia associated with the other firm characteristics do not differ across the subgroups, indicating that the relation between the value-premium and market expectation errors is not driven by other return effects. The sole exception is firm size in the case of specification (4) suggesting a statistically negative impact on expected returns when value and growth firms implied expectation is incongruent to underlying fundamentals.

5.4 Analysis of expectation errors from a present value perspective

We use a similar decomposition approach as in Cohen et al. (2003) to relate a firm's current BM ratio to its expected return, expected profitability and future BM ratio. Using equation (1), the firm-level variance of BM equals

$$\begin{aligned} \mathrm{var}(\widetilde{bm}) \approx \sum\nolimits_{j=0}^{N} \rho^{j} \mathrm{cov}(\tilde{\mathrm{r}}_{\mathrm{t+j}}, \widetilde{bm}_{t-1}) + \sum\nolimits_{j=0}^{N} \rho^{j} \mathrm{cov}(-\tilde{e}_{\mathrm{t+j}}, \widetilde{bm}_{t-1}) \\ + \ \rho^{N+1} \mathrm{cov}(\widetilde{bm}_{t+N}, \widetilde{bm}_{t-1}) \end{aligned} \tag{3}$$

Scaling both sides by the cross-sectional variance of $\widetilde{bm}_{t-1}$ gives each determinant's percentage weight, i.e. the extent to which differences in valuation ratios are associated with expected profitability and stock returns. We use tildes to denote cross-sectionally demeaned quantities in Equation (2) and use the Fama and MacBeth (1973) methodology to estimate the covariances in Equation (3).

Table 5.4 Decomposition of cross-sectional variation of BM ratios

	Estimated weightings ρ = 0.91, var(bm) = 0.69		
N	Expected returns	(−) Expected profitability	Future BM
1	-0.019 *(-1.83)*	0.105 *(18.91)*	0.907 *(100.87)*
2	0.018 (1.22)	0.190 (24.93)	0.772 (57.30)
3	0.039 *(2.06)*	0.256 *(27.85)*	0.673 *(38.04)*
4	0.056 (2.64)	0.309 (31.28)	0.595 (32.08)
5	0.070 *(2.97)*	0.356 *(33.97)*	0.525 *(28.08)*

The table shows the results of the variance decomposition of current BM ratios into future expected return, future expected profitability, and future BM ratio for the international (EAFE) sample during the period from 1990 to 2018. The first row presents a one-year decomposition, the second row a two-year decomposition, and so forth. Each estimate is the percentage of variation explained by the factor indicated by the column. We use the Fama and MacBeth (1973) methodology to estimate the covariances from cross-sectional demeaned regressions. Robust Newey and West (1987) t-statistics for the average estimates are given in parentheses.

Table IV shows the average coefficient estimates of the decomposition for all value and growth firms within our data sample to get a first impression what kind of information is priced into current BM ratios. The first column presents the increasing time horizon N, while the remaining three columns relate to the three components of the BM function presented in Equation (1). We estimate the average coefficients of equation (1) beginning at the one-year horizon ($N = 1$) up to a five-year horizon ($N = 5$) to examine how the decomposition results vary over time. At the one-year horizon, 91% of the cross-sectional variation in BM ratios is due to variation in future BM ratio, 11% is due to variation in expected profitability, and -2% is due to variation in expected returns. The negative sign on the expected return component indicates that an increase in expected returns entails, on average, an even stronger increase in cash flow expectations, thereby resulting in a lower BM ratio today. Not surprisingly, the statistical significance of these weights varies considerably. The table shows that the components concerning expected profitability and future BM ratio are statistically significant, whereas the negative variation with expected returns is not statistically different from zero. At the five-year horizon, about half of the variation (53%) is due to future BM ratios, 36% is due to profitability and only 7% is due to stock returns. Hence, most of the cross-sectional variation in BM ratios is still explained by future BM ratios. However, as the time horizon of our decomposition increases, the future BM component is steadily losing its importance and we observe a substantial increase in the fraction of variation in expected profitability that can be explained by variation in current BM ratios. The relative contribution of expected returns increases as well, however, plays only a minor role compared to expected profitability as the horizon lengthens. As a result, the three weights are statistically significant, despite considerable differences in the magnitude of these weights. Our baseline decomposition is consistent with prior U.S. evidence. Cohen et al. (2003) report that at the 5-year horizon, 50% of BM information is about future BM ratios, 38% about expected profitability, and the remaining 12% about expected returns. From a price-level perspective, our results suggest that most of a value (growth) stock's valuation is due to low (high) expected profitability rather than due to a high (low) expected return.

After having established that a major part of the cross-sectional variation in BM ratios can be in general attributed to variation in expected profitability as the horizon lengthens, we now examine the influence of a firm's FSCORE on the decomposition results of BM ratios. The way FSCORE is designed to capture a firm's fundamental strength, a high FSCORE strongly correlates with a firm's expected profitability. This raises the question whether the observed value premium between value firms with strong fundamentals and growth firms with weak fundamentals versus the non-existent value premium of value firms with weak fundamentals and growth firms with strong fundamentals is ultimately due to mispricing or just the result of differences in expected profitability.

Table 5.5 Conditional decomposition of cross-sectional variation of BM ratios

	No Expectation Errors ρ = 0.90, var(bm) = 0.55			Potential Expectation Errors ρ = 0.91, var(bm) = 0.69			Existent Expectation Errors ρ = 0.94, var(bm) = 0.51		
N	Expected returns	(−) Expected profitability	Future BM	Expected returns	(−) Expected profitability	Future BM	Expected returns	(−) Expected profitability	Future BM
1	-0.068	0.196	0.869	-0.024	0.104	0.913	0.175	0.000	0.819
	(-3.38)	*(20.89)*	*(55.50)*	*(-2.45)*	*(20.81)*	*(98.99)*	*(12.11)*	*(-0.03)*	*(51.77)*
2	-0.014	0.274	0.715	0.009	0.195	0.775	0.240	0.076	0.667
	(-0.68)	*(27.92)*	*(45.90)*	*(0.60)*	*(25.42)*	*(56.82)*	*(10.72)*	*(6.22)*	*(32.52)*
3	0.010	0.338	0.616	0.030	0.263	0.672	0.274	0.124	0.586
	(0.40)	*(28.28)*	*(33.12)*	*(1.49)*	*(26.68)*	*(36.79)*	*(10.40)*	*(7.38)*	*(27.18)*
4	0.012	0.401	0.551	0.051	0.315	0.591	0.302	0.158	0.535
	(0.44)	*(28.49)*	*(26.98)*	*(2.32)*	*(28.29)*	*(31.20)*	*(11.40)*	*(9.83)*	*(23.93)*
5	0.038	0.435	0.476	0.062	0.364	0.521	0.311	0.184	0.493
	(1.22)	*(28.77)*	*(21.91)*	*(2.54)*	*(29.59)*	*(27.98)*	*(10.85)*	*(10.53)*	*(20.13)*

The table shows the results for the variance decomposition of current BM ratios into expected return, expected profitability, and future BM ratio for the *no expectation errors*, *potential expectation errors*, and e*xistent expectation errors* portfolio during the sample period from 1990 to 2018. A stock is assigned to the *no expectation errors* portfolio if its BM is congruent with the fundamental strength (Growth × Strong or Value × Weak). A stock is assigned to the *existent expectation errors* portfolio if its BM is incongruent with the fundamental strength (Growth × Weak or Value × Strong). Growth and value stocks with medium FSCORE are assigned to the *potential expectation errors* portfolio. We estimate the covariances from cross-sectionally demeaned data. Robust Newey and West (1987) adjusted t-statistics for the average estimates are given in parentheses.

Table V shows the average coefficient estimates of the BM decomposition for our three subsamples. The results for the portfolio consisting of value and growth firms which are potentially exposed to expectation errors are similar to the decomposition results for the full sample shown in Table IV and confirm the observation that in general expected profitability is more informative about the variation in current BM ratios. However, when inspecting the two subgroups of value and growth firms with no expectation errors and existent expectation errors, respectively, strong differences become apparent. First, for value and growth stocks exposed to expectation errors, 31% of the variation in current BM ratios is due to expected stock returns at the five-year horizon. The corresponding number for value and growth stocks which are not exposed to expectation errors is only 4% and not statistically different from zero.

Second, for exposed stocks, the importance of expected profitability remains relatively low. Between the time horizon of one to five years, zero to 18% of the variation in current BM ratios is attributable to expected cash-flows, respectively. In contrast, for stocks without expectation errors, the contribution of expected profitability increases from 20% to 44% as the forecasting horizon lengthens from one to five years.

Given the fact that the return component in the decomposition is given by the product $b(\tilde{\mathrm{r}},\mathrm{N})\ \widetilde{bm}_{k,t-1}$ a large variation in expected returns is either the result of $b(\tilde{\mathrm{r}},\mathrm{N})$ or the result of a large variance in $\widetilde{bm}_{k,t-1}$.[40] This implies that our results could be driven by differences in the average cross-sectional variance of BM ratios in the three subsamples. Consequently, stocks in our mispriced portfolio show a stronger value premium because their BM ratios are more disperse compared to the other subsamples and not because their BM ratios are more informative about expected returns. However, the difference in variance between the non-mispriced portfolio and mispriced portfolio is not substantial in our case as the average cross-sectional variance of BM ratios equals 0.55 and 0.51 respectively.

[40] See equation A.7 in the Appendix.

5.5 Conclusion

This paper examines the market expectation errors hypothesis proposed by Piotroski and So (2012). Specifically, we analyze the previously documented interaction effects between FSCORE and a firm's BM ratio in the context of Cohen et al.'s (2003) present value model, which relates a firm's current BM ratio to its future BM ratio, expected return, and expected profitability. This methodology allows us to examine whether the observed return effect is the result of mispricing or due to differences in expected profitability.

In line with prior evidence, when expectations implied by a firm's BM ratio differ from a firm's underlying fundamental strength, i.e. high (low) BM firms with strong (weak) fundamentals, expectation errors arise which leads to a positive and significant realization of the value premium. If, however, firms with high (low) BM ratios and weak (strong) fundamentals are considered, there exists no value premium. All results are robust when simultaneously controlling for further firm characteristics that are known to be informative about the cross-section of expected returns.

Using the present value model proposed by Cohen et al. (2003), we show that variation in current BM ratios is mostly due to differences in expected cash-flows rather than expected returns. That means that the high (low) BM ratio of a value (growth) firm is rather due to low (high) expected profitability and not due to high (low) expected returns. However, taking the FSCORE into account, our decomposition results significantly vary. In the case of firms where BM implied expectations are incongruent to the underlying fundamental strength, the fraction explained by the expected return component significantly increases whereas the expected profitability component decreases. Contrary to that, for firms where BM implied expectations are aligned with a firm's fundamental strength, the effect of the expected return component almost diminishes. Our results suggest that the previously observed interaction effect of the BM ratio and FSCORE is indeed the result of mispricing which supports the proposed market expectation errors hypothesis proposed by Piotroski and So (2012).

Appendix

This appendix contains the derivation of Cohen et al.'s (2003) BM decomposition that shows how current BM ratio is related to future variables. We decompose the BM ratio of stocks to derive a cross-sectional link between current BM and future stock returns, future profitability, and future BM.

Following Cohen et al. (2003), the BM decomposition is derived from the accounting clean-surplus relation, which relates the annual change in book value of equity (BE) to earnings (X) fewer dividends (D) as follows:

$$BE_t - BE_{t-1} = X_t - D_t. \tag{A.1}$$

Frequent deviations in reported earnings, dividends, and book values are responsible that equation (A.1) is not always satisfied. Therefore, we construct the earnings as the sum of annual change in book value of equity plus dividends ($X_t = BE_t - BE_{t-1} + D_t$) to satisfy the clean-surplus assumption. Based on this approach, we define our log clean-surplus return on equity (e) as

$$e_t = log\left(1 + \frac{\Delta BE_t + D_t}{BE_{t-1}}\right). \tag{A.2}$$

We define bm_t as the log BM ratio and log stock return (r_t) as

$$r_t = \log\left(1 + \frac{ME_t + D_t}{ME_{t-1}}\right), \tag{A.3}$$

where ME_t is defined as market equity. Approximating stock and accounting returns by a Taylor series approximation, Cohen et at. (2003) show that,

$$bm_{t-1} = r_t - e_t + \rho bm_t + k_t, \tag{A.4}$$

where ρ represents a positive discounting parameter and k_t an approximation error. If $D_t \neq 0$, then $\rho < 1$, and $\rho = 1$ if $D_t = 0$. Multiplying both sides of (A.4) by the cross-sectional variance of bm_{t-1} eliminates the approximation error.

Then the variance decomposition can be obtained from (A.4) by taking the unconditional expectations:

$$\operatorname{var}(\widetilde{bm}) \approx \sum_{j=0}^{N} \rho^{j} \operatorname{cov}(\tilde{\mathrm{r}}_{\mathrm{t+j}}, \widetilde{bm}_{t-1}) + \sum_{j=0}^{N} \rho^{j} \operatorname{cov}(-\tilde{e}_{\mathrm{t+j}}, \widetilde{bm}_{t-1}) + \rho^{N+1} \operatorname{cov}(\widetilde{bm}_{t+N}, \widetilde{bm}_{t-1}) \tag{A.5}$$

Using tildes to denote cross-sectionally demeaned quantities, we scale both sides by the unconditional variance of $\widetilde{bm}_{t-1}$ which gives each determinant's percentage weight to current BM ratio, i.e., the extent to which differences in current valuation ratios are associated with future earnings and stock returns:

$$1 \approx \frac{\sum_{j=0}^{N} \rho^{j} \operatorname{cov}(\tilde{\mathrm{r}}_{\mathrm{t+j}}, \widetilde{bm}_{t-1})}{\operatorname{var}(\widetilde{bm})} + \frac{\sum_{j=0}^{N} \rho^{j} \operatorname{cov}(-\tilde{e}_{\mathrm{t+j}}, \widetilde{bm}_{t-1})}{\operatorname{var}(\widetilde{bm})} + \frac{\rho^{N+1} \operatorname{cov}(\widetilde{bm}_{t+N}, \widetilde{bm}_{t-1})}{\operatorname{var}(bm)}. \tag{A.6}$$

The equation above shows that the sum of these three factors is 1 so we can interpret these as the relative importance to cross-sectional differences in firms' BM ratio. We estimate each of the three contributing factors by regressing the following cross-sectional regressions with no intercept:

$$\begin{aligned} \sum_{j=0}^{N-1} \rho^{j} \tilde{r}_{k,t+j} &= b(\tilde{\mathrm{r}}, \mathrm{N})\, \widetilde{bm}_{k,t-1} + \varepsilon(\tilde{r}, N, k, t+N-1), \\ \sum_{j=0}^{N-1} \rho^{j} (-\tilde{e}_{k,t+j}) &= b(-\tilde{e}, \mathrm{N})\, bm_{k,t-1} + \varepsilon(-\tilde{e}, N, k, t+N-1), \\ \rho^{N} \widetilde{bm}_{k,t+N-1} &= b(\widetilde{bm}, \mathrm{N})\, \widetilde{bm}_{k,t-1} + \varepsilon(\widetilde{bm}, N, k, t+N-1). \end{aligned} \tag{A.7}$$

Finally, the estimated average coefficients in Equation (7) represent the percentage weight to current BM ratio, which are presented on the right-hand side of Equation (6).

Chapter 6
Conclusion

Momentum, value and investor sentiment are topics of broad interest and the debate about return behavior is ongoing. However, international literature on these topics is still scarce. This thesis contributes to the existing literature by examining novel momentum, as well as sentiment approaches in the broad set of international stock markets. For this purpose, the most recent trends and methods in asset pricing are considered and taken into account.

In the first paper, we provide new evidence about momentum and reversal in international stock markets. Using the firm characteristics size and book-to-market, we show that it is possible to ex-ante differentiate between stocks that gain from momentum and stocks that suffer from a reversal effect one year after portfolio formation. The premium associated with this adopted momentum strategy is significantly larger than the one of a standard momentum approach and robust after controlling for other return effects. Finally, we show that the observed interaction effect between a momentum portfolio and the aforementioned firm characteristics is the result of systematic mispricing.

The second research paper examines a new approach proposed by Aboody et al. (2018) to measure investor sentiment at the individual firm-level making use of overnight returns. Our results suggest that overnight returns are suitable to proxy for investor sentiment as they fulfil the following criteria: return persistence in the short run, the persistence is even stronger for firms that are harder to value, and firms with high overnight returns underperform in the long run. All three criteria are robust while controlling for other return characteristics in the cross-section, different time horizons, and different regions. After having established the suitability of overnight returns as a sentiment measure at the individual firm-level, we show that such a measure has explanatory power even beyond the well-known index proposed by Baker and Wurgler (2006) which proxies for market-wide sentiment.

The third research study examines previous U.S. findings of Byun et al. (2016) who propose a measure to capture continuing overreaction by market participants. Based on past returns and trading volumes, we show that the CO measure is also informative about expected returns in the broad cross-section of 15 developed capital markets in Europe over the sample period from 1992 to 2017. The premium associated with a long portfolio of high CO firms and a short portfolio of low CO firms cannot be explained by well-known cross-sectional return characteristics like firm size, book-to-market, or momentum, among others. Contrary to a standard momentum premium, which is associated with a negative reversal effect after one year, the premium associated with the novel measure does not suffer from a reversal.

The last paper investigates Piotroski and So's (2012) proposed market expectation errors hypothesis, which relates value to mispricing from a present value perspective. Using a comprehensive sample of international non-US equity markets, we show that the value premium is only present for firms where book-to-market implied expectations differ from a firm's underlying fundamental strength proxied by the FSCORE. If implied expectations are aligned with underlying fundamentals, no premium exists. The cross-sectional decomposition of book-to-market ratios into future book-to-market ratios, expected profitability, and expected returns reveals that the value premium, in general, is due to differences in expected profitability, challenging the notion by Piotroski and So (2012), who attribute value to mispricing. However, if we condition the present value model on expectation errors, we show that for firms where expectation errors exist, variation in book-to-market is mostly explained by expected returns and not expected profitability. Ultimately, this provides strong supportive evidence in favor of the mispricing-based explanation proposed by Piotroski and So (2012).

As clearly outlined throughout this thesis, the results provide valuable insights for academics in the context of the ongoing risk versus mispricing debate. Nonetheless, the results are interesting from a practitioner's perspective as well, especially in the context of an increasing amount of passive investment vehicles which are actually underperforming.

Investors implementing systematic momentum or value strategies should consider adopting the standard approaches in order to better capture cross-sectional mispricing. In the case of momentum strategies, a firm's size and book-to-market ratio can be incorporated to separate between stocks that gain from momentum and stocks that suffer from reversal. As a result, an enhanced momentum premium can be captured while simultaneously decreasing the needs for a frequent rebalancing which reduces trading costs. In the case of value strategies, the FSCORE can be used to construct a long-short portfolio, which consists of value and growth stocks exposed to market expectation errors. As the decomposition clearly showed, such an adopted strategy exploits cross-sectional mispricing and ultimately harvests a pure value premium.

Nevertheless, future research which puts a particular focus on the implementation from a market microstructure perspective of such strategies is welcome.

Overnight returns and continuing overreaction are both useful to better gauge investor sentiment and behavioral biases, respectively. In both cases, a good example of a beneficial application is momentum investing as outlined in the second and third research study presented in this thesis. However, from a top-level perspective, there exists a wide range of possible further applications. In general, all return effects related to behavioral biases can be enhanced using proxies to gauge investor sentiment. In addition, both measures provide useful tools to better distinguish between return effects which are possibly related to mispricing and return effects which can be explained from a risk perspective. However, in the age of big data, future research on investor sentiment should consider the incorporation of alternative data sets which could yield promising results.

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