Chapter 2

Cross-Country Composite Momentum

This chapter presents the first dissertation study which investigates the role of firm-specific characteristics for momentum to exist.

Zusatzmaterial online
Zusätzliche Informationen sind in der Online-Version dieses Kapitel (https://doi.org/10.1007/978-3-658-35479-4_2) enthalten.

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2.1 Introduction

Medium-term price continuation, commonly defined as momentum, is a widespread phenomenon in financial markets. It exists for individual stocks (Jegadeesh and Titman, 1993), for industry sectors (Moskowitz and Grinblatt, 1999), for style portfolios (Lewellen, 2002), in international equity markets (Rouwenhorst, 1998; Chui et al., 2010), and across asset classes (Bhojraj and Swaminathan, 2006; Menkhoff et al., 2012; Asness et al., 2013). Momentum also appears to be persistent over time, at least outside the U.S. stock market (Jegadeesh and Titman, 2001; McLean and Pontif, 2016; Green et al., 2017; Jacobs and Müller, 2020). Momentum strategies generate substantial long-short returns on paper, and they constitute an apparent violation of the efficient market hypothesis in its weak form (Fama, 1970). Hence, it is arguably not surprising that several theoretical approaches serve to explain the existence of momentum (Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999; Lee and Swaminathan, 2000; Vayanos and Woolley, 2013).

To test these competing momentum explanations empirically, a long strand of literature (Hong et al., 2000; Lee and Swaminathan, 2000; Zhang, 2006; Verardo, 2009; Da et al., 2014; Hillert et al., 2014) has analyzed the role of stock characteristics to potentially act as momentum "enhancing" drivers. As a result, a substantial amount of complex interaction patterns has emerged for momentum, with the underlying causes inconsistently subsumed by prior research. Explanation attempts vary from behavioral, limits-to-arbitrage to rational risk-based approaches, mirroring the wide range of existing theories on underyling causes of ordinary momentum itself.

Given this fragmentation and disparity in the enhanced momentum literature, our study aims to take a comprehensive and global perspective on how stock characteristics relate to momentum returns. While prior academic studies have focused on causes of global differences in ordinary momentum returns (e.g. Chui et al. (2010)), international studies upon (sources of) enhanced momentum have been neglected thus far. We believe that testing for sources of global differences in enhanced momentum, though, can offer valuable insights on the validity of theoretical explanations for ordinary momentum itself.

The rationale of our study is as follows. First, our study aims to be the first to analyze and document the existence, magnitude, and distribution of enhanced momentum returns across international equity markets. In this regard, we apply a wide range of stock characteristics which have been shown empirically to function as momentum enhancers and which have been published in top tier finance journals. Second, we combine the information of various firm-specific attributes within a single momentum enhancer at a time and test for the profitability of an investment strategy that takes advantage of our metric's information density. We refer to this metric as composite-momentum enhancer. Lastly, we strive to identify causes for global differences in both, ordinary and composite-enhanced momentum returns by applying a variety of country characteristics that serve as proxies for theoretical momentum explanations as outlined in Section 2.2. In doing so, we simultaneously analyze whether there exists a common root cause for ordinary momentum and composite-enhanced momentum returns.

To address these questions, we implement a 35 country-level analysis of 18 stock characteristics to test for their ability to enhance and predict momentum profits. Tested characteristics are based on a comprehensive review of the enhanced momentum literature and include: size, r-squared, turnover, age, analyst coverage, forecast dispersion, book-to-market, price, illiquidity, capital gains, information diffusion, failure probability, maximum daily return, equity duration, 52-week high price, asset growth, costs of goods sold, and revenue volatility.

Empirical findings provide evidence on the relevance of characteristics in enhancing momentum returns in international markets. The explanatory power to a large extent maintains after accounting for idiosyncratic volatility and extreme past returns as emphasized by Bandarchuk and Hilscher (2013). This finding reassures many of the conclusions taken from earlier momentum enhancing work. Out of a set of eighteen stock characteristics, we find particularly age, book-to-market, maximum daily return, R^2, information diffusion, and 52-week high or low price to matter for momentum profits. Intuitively, the importance of these characteristics seems consistent with behavioral explanation attempts as momentum appears to be stronger for hard-to-value firms (young firms with a low book-to-market ratio) with high information uncertainty (low R^2), and when investors are prone to underreaction (information diffusion; nearness to 52-week highs and lows). Beyond, our insights imply that a modest link between past returns, stock volatility, and momentum profits itself cannot explain enhanced momentum to its full extent.

To test if the link between momentum and stock characteristics is systematic and persistent, we analyze out-of-sample whether momentum profits can be predicted upon the basis of a composite-momentum metric. Specifically, we run rolling monthly multivariate regressions of momentum profits on characteristics. By applying average regression coefficients and constants on a five-year rolling basis, we use fitted values to predict momentum profits for the following month. When running univariate Fama and MacBeth (1973) regressions, we find that our predicted momentum measure is statistically significant at the 1%-level in explaining actual momentum profits, within 27 of our 35 countries investigated. Further, a momentum-neutral investment strategy that double-sorts on predicted momentum and past returns delivers monthly returns of 0.88% for the U.S. market (t-statistics: 3.13) and 1.14% for our international sample (t-statistics: 5.27). The statistical significance remains after accounting for idiosyncratic volatility and extreme past returns. Our findings thus suggest a strong and systematic link between firm-specific attributes and momentum.

We contribute to existing research in three ways. First, we add to the long-standing controversy on the behavioral versus rational debate of the underlying causes of momentum. Researchers have hitherto not reached a consensus on whether momentum can be ascribed to either rational or irrational investor behavior. Stock characteristics have become central to this controversy as they have proven to operate as momentum drivers. We add to this literature by providing empirical evidence that stock characteristics indeed have power in enhancing and even predicting momentum returns. Our cross-country analyses imply that both, ordinary and composite-enhanced momentum returns tend to be higher within countries that exhibit less trading frictions (i.e. developed markets with no short-sale constraints) and markets that exhibit less information opaqueness. This implies that ordinary and composite-enhanced momentum returns are higher whenever we observe markets with clear and easily accessible information. Simultaneously, we find composite-enhanced momentum returns to be higher in highly individualistic countries that simultaneously exhibit smaller degrees of power distance. Multivariate regressions reveal that our proxies for cultural differences are stronger and more significant in explaining both, ordinary and composite-enhanced momentum returns as opposed to proxies for market efficiency or slow information diffusion.

Second, we contribute to the general anomaly literature which has reemphasized data mining concerns recently (Lewellen et al., 2010; Cochrane, 2011; Harvey et al., 2016; Hou et al., 2020a). Specifically, by applying a (country, characteristics) 35x18 analysis, we conduct a broad international out-of-sample test and are able to detect which of the chosen characteristics are indeed major momentum enhancers across countries worldwide. This is relevant given that the importance of all of our chosen characteristics was originally detected by applying U.S. level data. Our study provides novel evidence on the robustness of our chosen set of characteristics in enhancing cross-sectional momentum returns. Overall, for the enhanced momentum literature our results do not suggest that "most claimed research findings...are likely false" (Harvey et al., 2016, p. 5). Rather, the momentum enhancing role of several characteristics such as firm age appears to be a consistent and persistent phenomenon in worldwide equity markets. This finding makes a data mining explanation for momentum less likely, but rather provides supportive evidence for behavioral explanation attempts (Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999).

Lastly, our insights have implications for the growing literature on international stock market segmentations. Results reported by former international out-of-sample tests concerning the ordinary momentum anomaly as conducted by Griffin et al. (2003), Chui et al. (2010), or Asness et al. (2013) often find substantial cross-country differences. Other studies related to the anomaly literature as the ones by Rapach et al. (2013) or Jacobs and Müller (2020) also detect geographic stock market segmentations. Our findings reveal apparently striking evidence for regional patterns between North America, Pacific, Europe, and Emerging Markets. Even within these regions, though, in part we still find a large variability of the importance of stock characteristics. While particular characteristics may not be a momentum enhancer in one country, they may play a big role in other, geographically related markets. From a practical perspective, this insight is also important for investors.

The paper proceeds as follows. Section 2.2 gives a brief overview of related literature and places our work within the current state of research. In Section 2.3, we outline the data set underlying our analysis, our construction of composite-momentum, and measurement of return dispersion. Section 2.4 reports our baseline results obtained from dependent double-sorting techniques and Fama-MacBeth regressions. In Section 2.5, we conduct cross-country analyses and illustrate drivers of global differences for both, ordinary and composite-enhanced momentum returns. Section 2.6 summarizes insights obtained from our study and concludes.

2.2 An Overview on Momentum Models and Enhanced Momentum Strategies

Existing theories on the underlying drivers of momentum are conflicting. For instance, Berk et al. (1999), Johnson (2002), Li (2018) as well as Vayanos and Woolley (2013) provide explanations complying with Fama's rational asset pricing paradigm.[1] Conversely, Barberis et al. (1998), Chan et al. (1996), Daniel et al. (1998), Hong and Stein (1999) as well as more recently Docherty and Hurst (2018) deliver plausible behavioral theories.[2]

Berk et al. (1999) argue that momentum results from changes in a firm's assets and growth options, leading to conditional expected returns. Johnson (2002) complements the work by Berk et al. (1999) by emphasizing that stochastic growth rates arising out of a time-varying exposure to firm-specific projects, account for momentum returns. Opposed to these firm-specific perspectives, Vayanos and Woolley (2013) emphasize the role of active fund flows in explaining momentum. Within their theoretical work, momentum arises if fund flows exhibit inertia and prices underreact to expected future flows. Gradual fund flows are assumed to be either driven by investor inertia or institutional constraints and are expected to be higher among high idiosyncratic volatility assets. More recently, Li (2018) establishes a neoclassical investment-based model arguing that productivity shocks, relative price shocks (indicating variations in the price of investment goods relative to that of consumption goods) as well as

[1] A non-exhaustive list on further explanations fitting rational asset pricing theory comprise works by Carhart (1997), Conrad and Kaul (1998), Chordia and Shivakumar (2002), Makarov and Rytchkov (2012), Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), Min and Kim (2016) as well as Maio and Philip (2018).

[2] Other behavioral attempts are for instance reported by Grinblatt and Han (2005), Baker and Wurgler (2007), and Banerjee et al. (2009).

investment frictions constitute underlying drivers of both, momentum returns and the value premium.

Contrarily, Chan et al. (1996) state that momentum results from a gradual diffusion of information into the market, particularly earnings-related news. Relatedly, Barberis et al. (1998) argue that momentum arises from the initial underreaction of a representative investor to news due to psychological biases such as representativeness and conservatism. The approach induced by Hong and Stein (1999) implies that information on a stock's fundamental value diffuses only gradually into the market. Hong and Stein (1999) distinguish between two types of investors: news watchers and momentum traders. News watchers underreact to new information, leading prices to adjust too slowly. Momentum traders exploiting these patterns in turn generate overreactions, leading to long-term reversals. In a similar manner, Docherty and Hurst (2018) argue that momentum is driven by myopic investors who overweight public information, leading to a slow diffusion of fundamental news. According to Docherty and Hurst (2018), myopic investment behavior is driven by short-term incentives as well as investor perceptions of other investors' beliefs similar to the beauty contest metaphor of Keynes (1936). Daniel et al. (1998) deliver a model in which momentum stems from intermediate market overreactions. Overconfidence and biased self-attribution causes investors to overweight (underweight) public information confirming (contradicting) their private stock evaluations. As uncertainty rises, psychological biases and thus mispricings are assumed to be strengthened.[3]

To test these competing explanations for the momentum effect empirically, numerous scholars have analyzed the ability of stock characteristics[4] to function as momentum enhancers. The rationale beyond is that certain firm attributes may indicate if a stock is prone to investor overreaction or underreaction (such as being "hard-to-value") or that certain firm attributes may signal specific risk features associated with momentum (such as suffering from "crash

[3]Still, one might argue that deviations from fundamentals should instantly be arbitraged away by investors exploiting mispricings. Earlier works (De Long et al., 1990; Shleifer and Vishny, 1997; Barberis et al., 1998) stress that because investor sentiments are at least partially unpredictable, arbitrageurs bear the risk of losing money in the short run, thus preventing them from pushing prices back to their fundamentals.

[4]Apart from firm-specific characteristics, another strand of literature analyzes macroeconomic aspects for momentum to exist. For instance, Avramov et al. (2016) study aggregate market liquidity whereas Min and Kim (2016) study economic downside risk.

risk”). Thus, to the extent this logic holds, conditioning on such firm-specific attributes should yield higher momentum returns. In the following, we refer to these studies as enhanced momentum literature.

In the enhanced momentum literature a large body of firm-specific attributes has been examined to test the validity of existing momentum theories. Empirical evidence is reported for characteristics such as size (Hong et al., 2000; Zhang, 2006), past trading volume (Lee and Swaminathan, 2000), analyst coverage (Hong et al., 2000; Zhang, 2006), age (Zhang, 2006), credit rating (Avramov et al., 2007), revenue volatility (Sagi and Seasholes, 2007), information diffusion (Da et al., 2014), and media coverage (Hillert et al., 2014).[5] Prior literature majorly attributes return enhancing abilities of characteristics to behavioral momentum theories. Still, empirical findings verify and augment opposing models. The difficulty lies in disentangling the sole effect of firm-specific attributes in enhancing momentum returns. Interaction patterns are complex and might either stem from the specific attribute itself, correlations with a multitude of other characteristics, omitted factors, or simply be interpreted in a variety of ways to either proxy for rational or behavioral theories, for market under- or overreactions.

Empirical evidence for the slow information diffusion model by Hong and Stein (1999) is for instance provided by Hong et al. (2000) and Avramov et al. (2007). Findings reported by Hoberg and Phillips (2018) are consistent with both, the model by Hong and Stein (1999) as well as the one proposed by Barberis et al. (1998). Contrarily, studies conducted by Zhang (2006), Chui et al. (2010), Hillert et al. (2014) as well as Avramov et al. (2016) rather provide support for the behavioral theory induced by Daniel et al. (1998). Sagi and Seasholes (2007) attribute their enhanced momentum findings to rational models proposed by Berk et al. (1999) and Johnson (2002) while, however, not exclusively precluding behavioral attempts. Beyond, works by Lee and Swaminathan (2000), George and Hwang (2004) as well as Da et al. (2014) do not fit neatly into existing frameworks, thus rather deliver own explanations for reported interaction patterns.

[5] A non-exhaustive list on further momentum-enhancing strategies include studies on illiquidity (Amihud, 2002), 52-week high price (George and Hwang, 2004), unrealized capital gains (Grinblatt and Han, 2005), R^2 (Hou et al., 2006), dispersion in analyst forecasts of earnings (Verardo, 2009), maximum daily return (Jacobs et al., 2016), and industry-based economic links (Hoberg and Phillips, 2018).

Instead of relating enhanced momentum returns to existing rational or behavioral theories, Bandarchuk and Hilscher (2013) offer an unprecedented explanation approach for why firm-specific attributes can be used to increase momentum returns. A major point of criticism invoked by them is that the bulk of previous enhanced momentum literature has centered on characteristics one at a time while characteristics tend to be correlated with each other as well as with past returns and idiosyncratic volatility.

Bandarchuk and Hilscher (2013, p. 824) argue that "recent winners are more likely to have high volatility. If volatility and characteristics are correlated, recent winners and losers have more extreme characteristics." They therefore stress that sorting on characteristics and past returns implies a hidden double-sort on volatility and past returns. A hidden sorting on volatility, in turn, implies a sort on more extreme past returns. Following this reasoning, double-sorting stocks on characteristics and past returns is assumed to lead to enhanced momentum returns solely due to this correlation. In line with this argumentation, the explanatory power of stock characteristics is expected to be substantially reduced once controlling for this effect. Bandarchuk and Hilscher (2013, p. 811) thus "suggest that a focus on the link between extreme past returns and momentum profits may be more appropriate." To the extent this reasoning holds, it poses a challenge for both, existing rational and behavioral momentum theories.[6]

Given this fragmentation and disparity in the enhanced momentum literature, our study aims to take a comprehensive and global perspective on how stock characteristics relate to momentum returns. While prior academic studies have focused on causes of global differences in ordinary momentum returns (e.g. Chui et al. (2010)), international studies upon (sources of) enhanced momentum have been neglected thus far. We believe that testing for sources of global differences in enhanced momentum, though, can offer valuable insights on the validity of theoretical explanations for ordinary momentum itself.

The rationale of our study is as follows. First, we aim to analyze and document the existence, magnitude, and distribution of enhanced momentum returns across international equity markets. In this regard, we apply previously reported stock characteristics which

[6] As remarked by Bandarchuk and Hilscher (2013), the theory closest to their logic is the one proposed by Vayanos and Woolley (2013) since they link momentum to high idiosyncratic volatility assets.

have been shown empirically to function as momentum enhancers and which have been published in top tier finance journals. Additionally, we account for potential interdependencies as reported by Bandarchuk and Hilscher (2013).

Second, we combine the information of various firm-specific attributes within a single momentum enhancer at a time and test for the profitability of an investment strategy that takes advantage of our metric's information density.

Lastly, we strive to identify causes for global differences in both, ordinary and composite-enhanced momentum returns by applying a variety of country characteristics that serve as proxies for theoretical momentum explanations as outlined in Section 2.2. In doing so, we simultaneously analyze whether there exists a common root cause for ordinary momentum and enhanced momentum returns.

2.3 Data and Methodology

2.3.1 Stock Market Data

We derive our data set from Datastream/Worldscope. The database is commonly employed for studies on momentum in international markets (Chui et al., 2010; Fama and French, 2012; Asness et al., 2013). Our sample period runs from January 1989 to June 2019. The initial starting date is the same as in the international study of Fama and French (2012) and illustrates a trade-off between maximizing the length of the time-series and maximizing the number of countries that can be included in the analysis. For some international markets, the starting date might vary due to availability of market data on Datastream or because of our screening criteria outlined in the following.

Stocks that at the beginning of each month are contained within the lowest NYSE market capitalization decile are excluded from our study. Following prior literature (Chui et al., 2010), this step ensures that momentum returns are not exclusively driven by small and illiquid stocks. To mitigate for the effect of outliers, returns are winsorized at the 0.1% and

99.9% levels. Each month, for each country we require at least 90 stocks to be available.[7] We justify this approach by the need of having sufficient observations to double-sort stocks into portfolios. If there are less than 180 months left fulfilling the criteria of 90 stocks or above for a country, we exclude the respective country from our analysis. We use a threshold of 180 months to ensure a minimum time-series of ten years within subsequent out-of-sample tests for which a lead time of 60 months is required as further outlined in Section 2.3.2.2.

Starting with 68 countries worldwide, our filtering criteria lead to a final sub-sample of thirty-five countries. The final countries included based of sufficient data availability are: Australia, Belgium, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hong Kong, Indonesia, India, Italy, Japan, Malaysia, Mexico, Netherlands, Norway, New Zealand, Pakistan, Philippines, Poland, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, and United States.[8] Taken all countries together, our final sample contains a total of 59,734 stocks of which 11,499 can be ascribed to the U.S. market.

Table 2.1 summarizes how firms and ordinary momentum returns are distributed among countries. Ordinary momentum returns are calculated going long the tertile of past return winners and short the tertile of past return losers. Excluding the most recent month, we use a six months period to calculate past returns and establish the momentum portfolios.

As shown in Table 2.1, largest country samples are obtained for the U.S. (11,499 firms), Japan (5,537 firms), and Canada (4,868 firms). The smallest sub-samples include New Zealand (186 firms), Mexico (202 firms), and Finland (225 firms). The worldwide percental market value (as of June 2019) accordingly is highest for the U.S. (38.20%), China (10.72%), and Japan (7.57%).

[7] This number constitutes a trade-off between maximizing the number of countries in the analysis and ensuring a minimum number of stocks within the enhanced momentum portfolios for reasons of liquidity and reliability. When applying 3x3 sorting technique, we are able to ensure an initial minimum number of 10 stocks within each sub-portfolio.

[8] In total, these 35 countries represent 95.07% of the total market capitalization of the larger pool of our initial 68 countries as of June 2019.

Table 2.1: Summary Statistics: Data Sample and Ordinary Momentum Returns

This table provides an overview of how firms and classical momentum profits are distributed among countries. We report the total absolute number of months, the total absolute number of firms as well as the average number of firms per month on a country-basis. We also state a country's worldwide percental market value as of June 2019. Additionally, we indicate summary statistics of ordinary momentum returns per country. We report mean, skewness, kurtosis, and sharpe ratios (SR) respectively. Ordinary momentum returns are calculated going long the tertile of past return winners and short the tertile of past return losers, indicating realized returns in t+1. Excluding the most recent month, we use a six months period to calculate past returns and establish the momentum portfolios. Sharpe ratios are annualized and computed using time-series averages of monthly momentum profits, risk-free rates, and standard deviations. The internationally pooled sample (International) contains all of our chosen countries apart from the U.S. market. Our sample period runs from M1:1989 to M6:2019. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

		Data Sample					Ordinary Momentum			
Country	Abbrev.	Beginning Month	Total Anomaly Months	Total # Firms	Average # Firms Per Month	% Market Value	Mean	Skew	Kurt	Sharpe Ratio
Australia	atl	01/1989	366	3,139	220.24	1.85%	1.16%***	-0.69	6.49	0.26
Belgium	bel	06/1997	265	231	60.82	0.49%	1.15%***	-0.33	7.09	0.21
Brazil	bra	06/2000	229	279	93.18	0.92%	1.19%***	-1.25	9.28	0.18
Canada	can	01/1989	366	4,868	338.40	2.73%	0.96%***	-1.08	8.41	0.17
Chile	chi	06/1998	242	241	71.25	0.30%	0.70%**	-1.77	11.07	0.14
China	chn	06/1996	277	3,877	1,392.16	10.72%	-0.29%	0.10	4.73	-0.11
Denmark	den	11/1989	356	325	53.29	0.50%	1.14%***	0.06	4.90	0.22
Finland	fin	06/1997	265	225	56.27	0.37%	0.35%	-0.54	5.20	0.04
France	fra	01/1989	366	1,743	276.53	3.61%	0.54%**	0.41	17.65	0.07
Germany	ger	06/1989	361	1,557	199.09	2.60%	0.67%***	-0.01	10.82	0.09
Greece	gre	06/1994	301	390	54.26	0.06%	0.71%	-1.35	14.62	0.06
Hong Kong	hkg	12/1990	343	2,288	318.80	4.42%	0.55%**	-1.92	12.26	0.07
Indonesia	ido	06/1993	308	687	89.52	0.65%	0.15%	-0.76	12.83	-0.01
India	ind	09/1992	322	3,708	273.15	2.88%	0.86%***	-1.46	13.25	0.12
Italy	ita	01/1989	366	622	138.92	0.87%	0.54%**	-0.05	9.18	0.07
Japan	jap	01/1989	366	5,537	1,426.32	7.57%	-0.16%	-0.72	9.41	-0.10
Malaysia	mal	09/1991	334	1,342	153.28	0.51%	0.53%	-6.29	77.71	0.05
Mexico	mex	06/1999	241	202	74.00	0.47%	0.71%**	-1.36	9.91	0.12
Netherlands	net	01/1989	366	313	81.87	0.79%	0.66%***	-0.22	5.68	0.09
Norway	nor	06/1994	301	516	72.02	0.41%	1.04%***	0.01	4.46	0.17
New Zealand	nzl	12/2001	206	186	35.04	0.14%	1.08%***	0.65	6.75	0.27
Pakistan	pak	06/2000	229	283	32.81	0.04%	0.79%**	-0.16	6.75	0.11
Philippines	phi	06/1996	277	294	55.19	0.36%	0.22%	-2.18	19.07	0.01
Poland	pol	06/2001	210	707	60.62	0.21%	1.11%***	-0.76	6.30	0.20
Singapore	sin	06/1992	325	1,084	132.20	0.78%	0.44%	-2.76	22.92	0.05
South Africa	soa	01/1990	354	857	116.20	0.65%	0.78%***	-0.64	5.05	0.12
South Korea	sok	06/1990	349	2,826	227.25	1.66%	0.33%	-0.99	14.70	0.02
Spain	spa	06/1990	349	370	93.70	1.00%	0.59%**	-0.98	8.99	0.08
Sweden	swe	06/1990	349	1,031	103.01	0.82%	0.58%**	-0.56	8.33	0.07
Switzerland	swi	01/1989	366	411	130.78	2.19%	0.91%***	-0.68	8.79	0.18
Taiwan	tai	06/1995	289	2,362	298.09	1.41%	0.28%	-1.14	8.79	0.02
Thailand	tha	01/1989	325	918	105.08	0.73%	0.61%	-2.27	17.10	0.05
Turkey	tur	06/1998	253	453	74.81	0.18%	-0.15%	-0.75	5.93	-0.06
United Kingdom	uni	01/1989	366	4,363	552.96	3.99%	0.93%***	-1.17	14.60	0.17
United States	usa	01/1989	366	11,499	2,411.37	38.20%	0.34%	-0.95	15.96	0.02
International	internat	01/1989	366	48,235	6,696.22	56.87%	0.50%**	-0.52	5.42	0.06

Lowest percental market values are reported for Pakistan (0.04%), Greece (0.06%), and New Zealand (0.14%). Average median market value per month ranges from lowest 521.95 million USD (Pakistan) to highest 1,486.77 million USD (Spain). Our internationally pooled sample comprising all of our sample countries with the exception of the U.S., contains 48,235 companies and illustrates 56.87% of worldwide percental market value as of June 2019. Ordinary monthly momentum returns on average are highest for Brazil (1.19%), Australia (1.16%), and Belgium (1.15%) and lowest for China (-0.29%), Japan (-0.16%), and Turkey (-0.15%). Within the U.S., ordinary momentum strategies yield average monthly returns of 0.34% with a standard deviation of 4.72%. At an internationally pooled basis, we obtain average monthly momentum returns of 0.50% with a standard deviation of 4.54%.

Overall, ordinary momentum returns tend to be negatively skewed, ranging from -6.29 (Malaysia) to -0.01 (Germany). Within Norway, Denmark, China, France, and New Zealand, though, monthly momentum returns are even slightly positively skewed, ranging from 0.01 (Norway) to 0.65 (New Zealand). Skewness of the U.S. amounts to -0.95, whereas it amounts to -0.52 for our internationally pooled sample. Our findings are in line with prior research, indicating for instance that momentum strategies do not tend to perform well within Asian countries (Griffin et al., 2003; Chui et al., 2010). Furthermore, in line with existing studies, we find that momentum returns tend to attenuate within the U.S. market (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). At an internationally pooled level, we observe a comparatively stable trend of momentum across time.

2.3.2 Composite Momentum

2.3.2.1 Selection and Measurement of Momentum-Enhancing Characteristics

To construct our composite momentum enhancer, we combine a variety of firm-specific attributes. Out of the anomaly literature, we choose a set of eighteen stock characteristics, most of which have been published in leading finance journals. Table 2.2 provides an overview of applied characteristics, their predicted way of interaction with momentum returns, respective reference studies as well as variable definitions.

Table 2.2: Overview of Applied Characteristics

This table summarizes characteristics applied within our analysis to enhance momentum profits, predicted momentum signs (whether or not expected correlations with momentum profits are either positive or negative), corresponding reference studies, and variable definitions, respectively.

Characteristic	Abbrev.	Sign	Reference Study	Definition
size	size	-	Hong et al. (2000)	market value of equity in USD
r-squared	R^2	-	Hou et al. (2006)	fraction of a firms return variance explained by the market factor
turnover	turn	+	Lee and Swaminathan (2000)	shares traded per month divided by the number of shares outstanding
age	age	-	Zhang (2006)	number of years, based on a firm's first appearance in Datastream
analyst coverage	nanalyst	-	Hong et al. (2000)	number of analysts covering stock
forecast dispersion	eps-disp	+	Zhang (2006)	dispersion in forecasted EPS
book-to-market	bm	-	Asness (1997)	book value of equity/market value of equity
price	price	-	Bandarchuk and Hilscher (2013)	price index not adjusted for stock splits in US-Dollar
illiquidity	illiquid	+	Amihud (2002)	average daily ratio of absolute stock return to dollar volume
failure probability	failure	+	Campbell et al. (2011)	financial distress measure
capital gains	cgs	+	Grinblatt and Han (2005)	capital gains of stock over previous five years
information diffusion	ID	-	Da et al. (2014)	continuous information proxy/continuous information arrival
maximum daily return	max-ret	-	Jacobs et al. (2016)	a stock's maximum daily return over the past one month
equity duration	dur	+	Dechow et al. (2004)	average maturity of a stock's expected future cash flows
52-week high price	P52-WH	+	George and Hwang (2004)	ratio of the current stock price to the maximum stock price of past 52 weeks
asset growth	ag	+	Cooper et al. (2008)	year-on-year percentage change in total assets
costs of goods sold	cogs	+	Sagi and Seasholes (2007)	costs of goods sold divided by a firms total assets
revenue volatility	rev-vola	+	Sagi and Seasholes (2007)	standard deviation of a stocks revenue growth throughout the past five years

As illustrated, we account for size (Hong et al., 2000), r-squared (Hou et al., 2006), turnover (Lee and Swaminathan, 2000), age (Zhang, 2006), analyst coverage (Hong et al., 2000), forecast dispersion (Zhang, 2006), book-to-market (Asness, 1997), price (Bandarchuk and Hilscher, 2013), illiquidity (Amihud, 2002), capital gains (Grinblatt and Han, 2005), information diffusion (Da et al., 2014), failure probability (Avramov et al., 2007; Campbell et al., 2008), maximum daily return (Jacobs et al., 2016), equity duration (Dechow et al., 2004; Jiang et al., 2005), 52-week high price (George and Hwang, 2004), asset growth (Cooper et al., 2008), costs of goods sold (Sagi and Seasholes, 2007), and revenue volatility (Sagi and Seasholes, 2007). Measurement details of our chosen set of characteristics follow the reference papers and are described in Table 2.2.

Most of these characteristics are expected to have the same impact on momentum profits for the long portfolio (recent winners) and the short portfolio (recent losers). For instance, we expect a stronger momentum trend for smaller firms, irrespective of whether they are recent winners or recent losers. However, for some characteristics the relation to momentum profits depends on whether we consider the long portfolio or the short portfolio. For instance, according to Grinblatt and Han (2005) low capital gains losers as well as high capital gains winners are likely to yield stronger momentum returns. Opposed to this, low capital gains winners and high capital gains losers are expected to generate lower momentum returns. The expected influence of capital gains is thus different for the long and the short side.

Therefore, with reference to the characteristics capital gains, maximum daily return, and 52-week high price, we adjust variables in the following way:[9]

$$char_{new} = (char_{ordinary} - median_{char}) \cdot sign(R_{t-6,t-1} - R_{median,t-6,t-1}) \tag{2.1}$$

The adjusted variables reverse the ranking for stocks which are part of the short side of the momentum portfolio, i.e. have a six-months return below the median. For instance, the expected influence of the adjusted variable capital gains is now positive for the long and short side of the momentum portfolio. This adjustment simplifies the structure of our tables

[9] The variable *information diffusion* is already adjusted in a similar manner by Da et al. (2014) and hence not included in this list.

and is necessary to conduct cross-sectional regressions of momentum profits on enhancing variables in the spirit of Bandarchuk and Hilscher (2013).

In line with respective reference studies in Table 2.2, we expect an inverse relationship between momentum and the following characteristics: size, r-squared, age, analyst coverage, book-to-market, price, information diffusion, and maximum daily return. To ease interpretations, we sort stocks in descending order according to these characteristics. That means, we always (double-) sort our stocks into portfolios such that long-short momentum returns should be highest in tertile 3 and lowest in tertile 1, if our initial expectations are met.

2.3.2.2 Methodological Setup

Given the fragmentation and disparity in the enhanced momentum literature, our study aims to take a comprehensive perspective on how stock characteristics relate to momentum returns. A central aspect within our study thus is combining the information of a variety of firm-specific attributes within a single metric. As emphasized, we refer to this metric as composite momentum enhancer.

We construct our composite momentum enhancer following procedures described by Lewellen (2015) and Green et al. (2017). Within these studies, authors have applied Fama-MacBeth regressions to forecast stock returns by combining various firm characteristics. To the best of our knowledge, our study is the first to apply a similar technique within the momentum literature.

In this regard, momentum profits are measured following Bandarchuk and Hilscher (2013), i.e. relative to whether or not a firm is able to outperform other stocks. Winner stocks are stocks having above-median returns. Loser stocks are stocks having below-median returns. Both, a stock's past and a stock's forward return are measured relative to respective medians. Accordingly, momentum profit is measured as a stock's forward return in relation to the median of all stock's forward returns, multiplied by a dummy variable, indicating whether the stock was a winner in the past six month (1) or a loser (-1):

$$R_{mom,t+1} = (R_{t+1} - R_{median,t+1}) \cdot sign(R_{t-6,t-1} - R_{median,t-6,t-1}) \tag{2.2}$$

By doing so, stocks exhibiting negative signs in both, past and forward periods, yield positive momentum profits.

We construct our composite momentum enhancer as follows. Each month, for each country, we divide each of the eighteen characteristics into tertiles. For our internationally pooled sample, characteristics tertiles are calculated transnationally on a monthly basis. Each month for each country, we then run multivariate regressions of momentum profits on all eighteen characteristics tertiles simultaneously. On a five-year rolling basis, we apply averages of obtained regression coefficients for each of our eighteen characteristics tertiles as well as the corresponding constant and thus predict momentum profits for the next month solely upon the basis of our chosen set of characteristics. By applying average regression coefficients and constants of the most recent 60 months, we predict momentum profits for the following investment period - exclusively upon the basis of our eighteen stock characteristics.

2.3.3 Extreme Past Returns and Idiosyncratic Volatility

To rule out the possibility that our results are (exclusively) driven by potential interdependencies between recent winners, firm characteristics, and idiosyncratic volatility, we include two additional control variables within our study as in the spirit of Bandarchuk and Hilscher (2013). We do so by firstly measuring past returns in a direct way: Each month t, we calculate a stock's momentum strength in the following way:

$$Mom\_strength_{i,t} = exp(|r_{i,t-6,t-1} - r_{median,t-6,t-1}|) - 1 \tag{2.3}$$

In equation (1), a stock's cumulative return over the past six months is denoted as log return. We subtract the country's median stock return from individual stock returns and take the absolute value. Following this approach, momentum strength indicates the extent to which past returns are extreme, i.e. both extreme losers as well as extreme winners have a higher momentum strength (Bandarchuk and Hilscher, 2013).

Besides extreme past returns, we account for firm-specific volatility. Idiosyncratic volatility is measured using regression residuals of ordinary monthly returns over the previous twelve months on the market factor (CAPM). Market returns indicate monthly excess returns on the market. We use the country-specific MSCI index as market reference and the one-month U.S. treasury bill rate as proxy for the risk-free rate.

2.4 Empirical Results

2.4.1 Portfolio Returns of Single Momentum-Enhancing Trading Strategies

We start by demonstrating that double-sorting stocks on characteristics and past returns leads to enhanced momentum profits and thus that characteristics have the potential to function as momentum enhancers within international equity markets. We do so by applying dependent and equally-weighted sorting techniques. In this section, we use "ordinary" double-sorts, which means we neither control for momentum strength and idiosyncratic volatility nor apply our composite-momentum metric.

At the end of each month, for each country we sort each characteristic into tertiles. Within each characteristic tertile, we calculate ordinary momentum strategies. This means we go long the tertile of past return (t-6,t-1) winners and short the tertile of past return (t-6,t-1) losers (P3-P1). We then calculate the differences between momentum returns of highest and lowest characteristics tertiles. With regard to size, r-squared, age, analyst coverage, book-to-market, price, information diffusion, and maximum daily return, we sort stocks in descending order because these stocks are supposed to weaken momentum profits as described above. For every characteristic, this procedure ensures highest (lowest) expected momentum returns in tertile 3 (1). Table 2.3 summarizes monthly returns obtained from ordinary double-sorts for each country-characteristic combination respectively.

Table 2.3: Unconditional Returns of Enhanced Momentum Strategies

This table reports average monthly returns obtained from ordinary double-sorts on IVOL, momentum strength, or characteristics (first-sort) and on past returns (second-sort). At the end of each month, for each country we sort each characteristic into tertiles. Within each characteristic tertile, we calculate ordinary momentum strategies. That is, we go long the tertile of past return (t-6,t-1) winners and short the tertile of past return (t-6,t-1) losers (P3-P1). We then calculate the differences between momentum returns of highest and the lowest characteristics tertiles. For IVOL, turnover, forecast dispersion, illiquidity, capital gains, failure probability, equity duration, 52-week high price, asset growth, costs of goods sold, and revenue volatility ascending order (Q3-Q1) is used. For size, r-squared, age, analyst coverage, book-to-market, price, information diffusion, and maximum daily return, stocks are sorted in descending order (Q1-Q3). The sample runs from M1:1989 to M6:2019. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

Panel A: North America, Japan, Pacific							
	North America		Japan	Pacific			
	can	usa		atl	nzl	hkg	sin
IVOL	1.36%***	1.04%***	0.24%	1.65%***	0.63%	0.53%	0.16%
	(4.16)	(4.61)	(1.43)	(4.94)	(0.89)	(1.39)	(0.43)
mom_str	1.43%***	0.90%***	0.05%	1.88%***	1.63%**	0.47%	0.44%
	(4.07)	(2.75)	(0.18)	(5.25)	(2.62)	(1.11)	(1.14)
size	0.97%***	0.52%***	-0.12%	1.39%***	0.99%**	0.21%	0.43%
	(3.88)	(3.12)	(-0.73)	(4.47)	(2.10)	(0.59)	(1.24)
R^2	0.41%	0.37%**	0.35%**	1.27%***	1.31%**	0.89%**	1.06%***
	(1.59)	(2.09)	(2.54)	(4.42)	(2.39)	(2.45)	(2.97)
turn	-0.03%	0.51%**	-0.09%	-0.84%***	0.69%	-0.10%	-0.41%
	(-0.10)	(2.14)	(-0.40)	(-2.89)	(1.21)	(-0.26)	(-1.02)
age	0.90%***	1.03%***	0.71%*	1.46%***	-0.08%	0.75%*	0.89%**
	(3.02)	(4.32)	(1.82)	(5.09)	(-0.12)	(1.93)	(2.50)
nanalyst	0.75%***	0.40%**	0.03%	1.34%***	-0.15%	-0.23%	0.27%
	(2.80)	(2.48)	(0.18)	(4.70)	(-0.27)	(-0.69)	(0.72)
eps-disp	0.66%**	0.43%**	-0.02%	1.09%***	0.49%	0.72%**	-0.55%
	(2.08)	(2.19)	(-0.17)	(3.36)	(0.81)	(2.26)	(-1.57)
bm	0.88%***	0.72%***	0.74%***	0.49%	-0.29%	0.39%	0.87%**
	(2.78)	(3.12)	(4.48)	(1.38)	(-0.47)	(1.06)	(2.62)
price	0.94%***	0.28%	-0.80%***	0.42%	-0.11%	(0.00)	0.18%
	(3.17)	(1.28)	(-4.50)	(1.39)	(-0.21)	(0.37)	(0.56)
amihud	0.56%**	0.20%	0.15%	1.26%***	0.70%	0.42%	1.06%***
	(2.12)	(1.05)	(0.70)	(4.18)	(1.09)	(1.20)	(2.67)
cgs	0.78%*	-0.12%	-0.26%	0.75%**	0.97%*	0.82%*	0.11%
	(1.90)	(-0.29)	(-0.86)	(2.16)	(1.65)	(1.85)	(0.27)
ID	0.84%***	0.06%	0.04%	0.94%***	0.33%	1.15%***	-0.42%
	(2.72)	(0.24)	(0.23)	(3.30)	(0.52)	(3.35)	(-1.24)
failure	0.53%	0.45%**	-0.37%**	0.34%	-1.18%*	0.35%	-0.38%
	(1.62)	(2.06)	(-2.43)	(1.11)	(-1.72)	(0.77)	(-0.86)
max-ret	0.39%	0.73%*	0.76%**	0.02%	0.61%	1.08%**	-0.04%
	(1.16)	(1.66)	(2.62)	(0.07)	(1.12)	(2.18)	(-0.11)
dur	0.80%***	1.09%***	0.27%**	0.73%**	-0.92%	0.59%*	0.46%
	(2.93)	(4.75)	(2.00)	(2.65)	(-1.36)	(1.82)	(1.34)
p52-wh	1.24%***	0.12%	-0.06%	1.33%***	1.53%***	1.53%***	0.34%
	(3.18)	(0.24)	(-0.14)	(3.86)	(2.96)	(2.68)	(0.81)
ag	0.69%***	0.38%**	0.72%***	1.22%***	0.70%	0.46%	0.41%
	(2.83)	(2.38)	(5.66)	(4.29)	(1.12)	(1.35)	(1.28)
cogs	-0.20%	-0.21%	-0.23%*	0.17%	1.25%**	1.06%***	1.44%***
	(-0.70)	(-1.07)	(-1.87)	(0.59)	(2.14)	(2.94)	(3.78)
rev-vola	0.43%	0.37%***	0.38%***	0.15%	-0.08%	-0.27%	-0.31%
	(1.56)	(3.00)	(3.34)	(0.58)	(-0.14)	(-0.88)	(-0.87)
# t-stat>+2	13	13	6	13	5	6	5

Table 2.3 (Cont'd)

	Panel B: Europe											
	bel	den	fin	fra	ger	ita	net	nor	spa	swe	swi	uni
IVOL	1.61%***	0.53%	-0.30%	0.42%	1.15%***	0.85%**	0.98%**	1.08%**	0.70%*	0.74%*	0.61%**	1.18%***
	(2.84)	(1.20)	(-0.62)	(1.37)	(3.49)	(2.46)	(2.51)	(2.05)	(1.81)	(1.90)	(2.46)	(4.81)
mom_str	2.03%***	1.35%***	0.36%	0.98%***	1.30%***	0.74%*	0.99%**	1.66%***	0.96%**	0.38%	0.96%***	1.38%***
	(3.58)	(3.20)	(0.63)	(2.82)	(3.68)	(1.87)	(2.42)	(3.10)	(2.34)	(0.78)	(3.30)	(4.61)
size	1.14%**	0.57%	0.16%	0.62%***	0.46%	0.18%	1.31%***	0.56%	0.56%	0.48%	0.53%**	0.84%***
	(2.40)	(1.33)	(0.32)	(2.72)	(1.60)	(0.61)	(3.97)	(1.11)	(1.45)	(1.22)	(2.15)	(4.46)
R^2	1.18%**	0.68%	0.48%	0.32%	-0.06%	0.48%	0.86%**	1.25%**	0.38%	0.44%	0.91%***	1.14%***
	(2.62)	(1.51)	(0.92)	(1.18)	(-0.18)	(1.61)	(2.58)	(2.19)	(1.05)	(1.12)	(3.66)	(5.69)
turn	0.08%	-0.05%	0.11%	-0.14%	0.36%	0.42%	-0.27%	0.02%	0.18%	-0.42%	-0.11%	-0.45%**
	(0.16)	(-0.11)	(0.20)	(-0.39)	(1.15)	(1.22)	(-0.70)	(0.04)	(0.49)	(-0.98)	(-0.40)	(-2.26)
age	1.59%***	1.06%*	0.43%	0.59%**	1.38%***	0.18%	-0.88%	0.75%	0.23%	1.12%***	1.30%***	1.09%***
	(3.46)	(1.89)	(0.79)	(2.25)	(4.44)	(0.53)	(-0.97)	(1.45)	(0.49)	(2.80)	(4.39)	(3.74)
nanalyst	0.69%	0.44%	0.13%	0.29%	-0.30%	0.29%	0.87%**	0.59%	0.82%**	1.01%**	0.79%***	1.16%***
	(1.49)	(1.12)	(0.26)	(1.16)	(-0.98)	(1.15)	(2.37)	(1.14)	(2.28)	(2.57)	(2.97)	(5.30)
eps-disp	1.27%**	-0.23%	-0.33%	0.39%	-0.13%	-0.12%	0.95%**	0.74%	0.49%	-0.24%	-0.05%	0.53%**
	(2.12)	(-0.52)	(-0.69)	(1.36)	(-0.38)	(-0.36)	(2.41)	(1.53)	(1.33)	(-0.56)	(-0.19)	(2.46)
bm	0.89%	1.07%**	0.05%	0.35%	0.92%***	0.55%*	0.78%**	0.67%	0.08%	1.38%***	0.85%***	0.85%***
	(1.62)	(2.29)	(0.11)	(1.25)	(3.29)	(1.85)	(2.16)	(1.21)	(0.22)	(3.47)	(3.57)	(3.81)
price	0.90%*	0.03%	0.52%	-0.04%	0.59%*	-0.12%	0.35%	0.83%	0.22%	-0.59%	0.49%*	0.51%**
	(1.81)	(0.06)	(1.08)	(-0.13)	(1.71)	(-0.39)	(0.91)	(1.53)	(0.59)	(-1.38)	(1.80)	(2.56)
amihud	0.58%	0.29%	0.04%	0.47%	-1.15%	-0.21%	1.00%***	0.19%	0.10%	0.51%	0.77%***	1.02%***
	(1.06)	(0.64)	(0.07)	(1.55)	(-1.23)	(-0.51)	(2.82)	(0.33)	(0.25)	(1.36)	(2.73)	(2.80)
cgs	0.62%	-0.20%	-0.01%	0.22%	1.35%**	1.26%***	1.35%***	1.45%**	0.78%*	0.52%	0.40%	0.77%**
	(1.03)	(-0.38)	(-0.01)	(0.58)	(2.05)	(2.86)	(3.02)	(2.37)	(1.72)	(1.03)	(1.31)	(2.29)
ID	0.07%	0.22%	-0.04%	0.20%	1.01%***	0.04%	0.36%	0.63%	0.37%	0.31%	0.19%	0.43%*
	(0.13)	(0.50)	(-0.07)	(0.75)	(3.14)	(0.12)	(0.89)	(1.22)	(0.91)	(0.76)	(0.80)	(1.95)
failure	0.93%**	-0.77%	0.69%	-0.28%	0.08%	0.04%	0.50%	1.04%*	0.40%	0.18%	0.70%**	0.18%
	(1.98)	(-1.50)	(1.23)	(-0.85)	(0.23)	(0.11)	(1.29)	(1.87)	(0.96)	(0.45)	(2.50)	(0.81)
max-ret	0.92%	-0.18%	0.00%	1.04%***	1.09%**	0.70%*	0.75%*	0.77%	0.33%	1.23%***	0.55%	0.01%
	(1.59)	(-0.37)	(-0.01)	(3.01)	(2.57)	(1.93)	(1.72)	(1.27)	(0.79)	(2.67)	(1.63)	(0.03)
dur	1.38%***	-0.18%	1.18%**	0.49%	0.54%	0.50%*	0.82%**	1.51%***	-0.17%	1.16%***	0.96%***	0.91%***
	(2.70)	(-0.39)	(2.35)	(1.59)	(1.62)	(1.72)	(2.20)	(3.07)	(-0.49)	(2.79)	(3.70)	(4.02)
p52-wh	1.47%**	1.51%***	0.13%	0.03%	1.20%**	0.71%	1.07%**	1.44%**	1.46%***	0.30%	0.74%*	1.35%***
	(2.27)	(3.15)	(0.19)	(0.06)	(2.63)	(1.54)	(2.12)	(2.11)	(2.80)	(0.63)	(1.89)	(3.91)
ag	0.55%	0.46%	0.72%	0.65%**	0.73%**	0.10%	0.36%	1.02%*	0.89%**	1.32%***	0.41%*	0.75%***
	(0.99)	(0.96)	(1.42)	(2.44)	(2.55)	(0.35)	(1.00)	(1.91)	(2.49)	(3.23)	(1.71)	(4.02)
cogs	0.11%	-0.65%	-0.72%	0.44%**	-0.23%	-0.59%*	-0.65%*	-0.13%	-0.41%	0.11%	-0.07%	-0.14%
	(0.21)	(-1.23)	(-1.41)	(1.97)	(-0.75)	(-1.89)	(-1.74)	(-0.22)	(-1.10)	(0.28)	(-0.25)	(-0.66)
rev-vola	0.40%	0.31%	0.68%	0.12%	0.32%	0.06%	0.42%	-0.01%	0.04%	0.67%*	-0.23%	0.69%***
	(0.80)	(0.64)	(1.30)	(0.55)	(1.11)	(0.21)	(1.03)	(-0.02)	(0.09)	(1.69)	(-0.89)	(3.34)
# t-stat>+2	8	3	1	5	9	2	11	6	4	6	10	15

Table 2.3 (Cont'd)

	Panel C: Emerging Markets															
	bra	chi	chn	gre	ind	ido	mal	mex	pak	phi	pol	soa	sok	tai	tha	tur
IVOL	0.04%	1.03%	0.50%*	-0.60%	0.46%	-0.91%	-0.43%	0.27%	-0.04%	0.07%	0.73%	1.04%**	0.50%	0.88%**	-0.62%	-0.50%
	(0.06)	(1.55)	(1.76)	(-0.72)	(1.09)	(-0.94)	(-1.28)	(0.54)	(-0.05)	(0.11)	(1.32)	(2.49)	(1.07)	(2.53)	(-1.18)	(-0.89)
mom_str	-1.02%	0.71%	-0.03%	0.68%	0.89%**	0.09%	-0.03%	1.09%**	0.38%	-0.67%	1.43%**	1.92%***	-0.28%	0.80%*	0.12%	-0.17%
	(-1.37)	(1.31)	(-0.08)	(0.78)	(2.02)	(0.10)	(-0.07)	(1.97)	(0.43)	(-0.77)	(2.30)	(4.51)	(-0.53)	(1.93)	(0.19)	(-0.27)
size	0.68%	0.13%	0.05%	-0.54%	0.44%	0.81%	-0.23%	0.60%	-0.91%	0.16%	0.34%	0.39%	0.59%	-0.15%	-0.81%	1.17%*
	(1.06)	(0.24)	(0.14)	(-0.76)	(1.12)	(1.10)	(-0.67)	(1.15)	(-0.96)	(0.23)	(0.60)	(1.08)	(1.22)	(-0.44)	(-1.05)	(1.71)
R^2	0.61%	0.02%	-0.48%	1.70%**	0.32%	-2.21%	0.89%**	0.15%	0.73%	0.30%	0.59%	1.53%***	-0.26%	0.75%**	0.35%	-0.81%
	(0.92)	(0.04)	(-1.45)	(2.07)	(0.83)	(-2.38)	(2.50)	(0.29)	(0.78)	(0.39)	(1.01)	(3.46)	(-0.59)	(2.52)	(0.61)	(-1.26)
turn	1.20%*	0.55%	0.69%**	-0.50%	0.06%	2.12%**	-0.96%**	0.46%	-1.02%	-1.31%*	-0.08%	-0.33%	0.43%	1.16%***	-0.41%	0.00%
	(1.92)	(0.91)	(1.99)	(-0.56)	(0.14)	(2.07)	(-2.55)	(0.92)	(-1.10)	(-1.73)	(-0.12)	(-0.81)	(1.00)	(3.50)	(-0.64)	(0.00)
age	1.54%**	0.21%	0.68%**	0.59%	-0.32%	0.11%	0.58%*	0.46%	-0.77%	-1.38%*	-0.09%	0.94%**	0.23%	0.52%	0.00%	-0.06%
	(2.63)	(0.22)	(2.19)	(0.54)	(-0.99)	(0.14)	(1.67)	(0.95)	(-0.61)	(-1.65)	(-0.15)	(2.28)	(0.58)	(1.50)	(-0.01)	(-0.09)
nanalyst	0.27%	-0.17%	-0.68%	-0.34%	0.46%	-1.51%*	-0.31%	0.51%	0.10%	0.01%	0.44%	0.47%	-0.06%	-0.27%	-0.18%	-0.19%
	(0.40)	(-0.33)	(-1.48)	(-0.39)	(1.31)	(-1.69)	(-0.79)	(1.07)	(0.14)	(0.01)	(0.80)	(1.14)	(-0.14)	(-0.92)	(-0.31)	(-0.31)
eps-disp	0.95%	0.84%	0.75%	-0.48%	0.52%	-0.32%	-0.77%**	0.74%	-0.28%	0.15%	1.52%**	0.58%	0.84%*	-0.29%	-0.05%	1.02%
	(1.11)	(1.45)	(1.02)	(-0.52)	(1.18)	(-0.40)	(-2.07)	(1.26)	(-0.34)	(0.23)	(2.31)	(1.39)	(1.91)	(-0.81)	(-0.09)	(1.55)
bm	1.00%	-0.51%	-0.32%	1.05%	1.41%***	-1.14%	1.08%***	0.99%**	0.04%	-0.01%	-0.33%	0.48%	0.00%	0.96%**	1.08%*	-0.28%
	(1.47)	(-1.21)	(-0.99)	(1.13)	(3.46)	(-1.06)	(3.21)	(1.99)	(0.04)	(-0.01)	(-0.55)	(1.35)	(0.00)	(2.58)	(1.66)	(-0.47)
price	-0.74%	-0.16%	-0.71%*	-1.11%	-1.11%**	-1.14%	-0.81%**	0.49%	-0.96%	-0.81%	-0.04%	0.59%	0.09%	-1.22%***	-0.11%	-0.10%
	(-1.13)	(-0.29)	(-1.80)	(-1.46)	(-2.58)	(-1.31)	(-2.02)	(1.04)	(-1.15)	(-1.04)	(-0.06)	(1.38)	(0.20)	(-3.32)	(-0.19)	(-0.15)
amihud	0.00%	0.10%	-0.06%	0.93%	0.80%**	-0.87%	0.56%*	-0.17%	0.41%	1.26%*	-0.47%	0.30%	-0.36%	-0.24%	-0.49%	1.03%
	(0.00)	(0.19)	(-0.16)	(1.01)	(2.08)	(-0.96)	(1.71)	(-0.31)	(0.43)	(1.65)	(-0.65)	(0.71)	(-0.73)	(-0.71)	(-0.80)	(1.46)
cgs	0.97%	0.36%	-1.59%***	1.07%	1.12%**	0.12%	-0.37%	-0.01%	-0.33%	-0.18%	0.21%	0.35%	0.40%	1.33%***	1.84%***	-0.71%
	(1.27)	(0.70)	(-2.79)	(1.05)	(2.20)	(0.12)	(-0.95)	(-0.02)	(-0.40)	(-0.21)	(0.32)	(0.75)	(0.71)	(2.72)	(3.00)	(-1.08)
ID	1.45%**	0.40%	-0.17%	0.07%	0.98%**	0.71%	-0.13%	0.00%	2.54%***	0.70%	1.49%**	0.82%**	0.01%	0.90%***	-0.29%	0.75%
	(2.19)	(0.90)	(-0.48)	(0.09)	(2.41)	(0.74)	(-0.32)	(0.00)	(3.09)	(1.00)	(2.51)	(2.23)	(0.01)	(2.67)	(-0.52)	(1.00)
failure	0.31%	0.43%	-0.39%	0.35%	-0.66%	-1.15%	-0.59%	0.07%	0.12%	0.28%	0.50%	0.55%	0.12%	-0.10%	-0.40%	-0.90%
	(0.41)	(0.82)	(-1.06)	(0.50)	(-1.48)	(-0.95)	(-1.39)	(0.13)	(0.10)	(0.21)	(0.59)	(1.28)	(0.32)	(-0.26)	(-0.57)	(-1.53)
max-ret	-1.54%**	-0.48%	1.69%***	1.83%**	0.66%	0.29%	0.34%	-0.63%	-1.46%	1.70%**	0.27%	0.48%	0.61%	0.61%	-0.36%	1.10%
	(-2.23)	(-0.80)	(3.82)	(2.30)	(1.48)	(0.27)	(0.79)	(-1.01)	(-1.57)	(2.21)	(0.44)	(1.12)	(1.40)	(1.39)	(-0.64)	(1.63)
dur	-0.59%	0.00%	-0.54%*	0.57%	0.65%	-1.46%	-0.03%	-0.11%	-0.05%	-0.72%	0.87%	0.37%	0.79%*	-0.02%	0.60%	-0.36%
	(-0.91)	(0.00)	(-1.85)	(0.65)	(1.59)	(-1.48)	(-0.11)	(-0.22)	(-0.06)	(-1.03)	(1.37)	(0.96)	(1.92)	(-0.09)	(1.29)	(-0.69)
p52-wh	-1.72%**	0.16%	-0.92%*	0.82%	1.08%**	1.31%	0.40%	-0.49%	1.33%*	0.18%	0.70%	0.91%*	0.22%	1.14%**	1.30%	0.15%
	(-2.11)	(0.27)	(-1.78)	(0.83)	(2.22)	(1.35)	(0.81)	(-0.76)	(1.66)	(0.21)	(1.10)	(1.91)	(0.34)	(2.16)	(1.63)	(0.21)
ag	0.37%	-0.60%	0.63%**	0.62%	0.49%	0.22%	-0.27%	-0.06%	-0.90%	0.13%	0.66%	0.21%	0.07%	0.95%***	-0.18%	-0.61%
	(0.57)	(-1.06)	(2.33)	(0.83)	(1.15)	(0.29)	(-0.72)	(-0.11)	(-0.98)	(0.21)	(1.12)	(0.56)	(0.18)	(2.90)	(-0.32)	(-1.02)
cogs	0.67%	0.19%	0.13%	0.96%	0.43%	0.29%	0.87%***	-0.75%	0.26%	0.22%	-0.60%	1.00%**	0.84%*	0.82%**	0.44%	1.43%**
	(0.98)	(0.36)	(0.46)	(1.58)	(1.24)	(0.43)	(2.68)	(-1.49)	(0.30)	(0.24)	(-0.83)	(2.34)	(1.75)	(2.51)	(0.78)	(2.20)
rev-vola	1.00%	-0.69%	-0.05%	-1.27%	0.31%	1.85%*	0.15%	0.53%	0.49%	0.07%	0.50%	0.33%	0.19%	-0.10%	-0.08%	1.49%**
	(1.29)	(-1.63)	(-0.11)	(-1.58)	(0.69)	(1.73)	(0.41)	(0.97)	(0.50)	(0.09)	(0.83)	(0.73)	(0.49)	(-0.36)	(-0.16)	(2.30)
# t-stat>+2	2	0	3	2	6	1	3	0	1	1	3	6	0	9	1	2

As shown in Table 2.3, double-sorting on characteristics and past returns best functions within the United Kingdom, being followed by Australia, Canada, the United States, Netherlands, and Switzerland.[10] On the other hand, the profitability of enhancing strategies deviates for Asian countries. In Japan, for instance, double-sorting on price and past returns leads to a statistically significant monthly negative return of 0.80% (t-statistics of -4.50). This finding implies that the characteristic *price* has a reversed effect within Japan, yet is per se significant in enhancing momentum returns when applying ascending rather than descending sorting technique (Q3-Q1). Within other Asian countries, though, enhancing strategies neither work in both directions, i.e. they neither yield statistically significant positive nor negative returns. This for instance holds for South Korea, Pakistan, the Philippines or Thailand. This finding is in line with existing literature stating that within Asian countries ordinary momentum strategies do not tend to perform well either (Griffin et al., 2003; Chui et al., 2010). Few characteristics occasionally, though, seem to matter even across multiple Asian countries. In Japan, Hong Kong, Malaysia, Singapore, and Taiwan, for instance, R^2 matters strongly (t-statistics greater than two). In a similar vein, we find a strong segmentation within European countries. Whereas double-sortings perform well within United Kingdom, Netherlands, Switzerland, Belgium, and Germany, they hardly function within Denmark, Finland or Italy.

Highest returns on average are obtained when double-sorting on momentum strength (average monthly excess return of 0.74%), 52-week high price (0.69%) as well as r-squared (0.51%), book-to-market (0.51%), and age (0.51%). In line with Bandarchuk and Hilscher (2013), idiosyncratic volatility also appears to be an important momentum enhancer with an average return of 0.50% per month across all countries. Lowest mean returns result from double-sorts on price (-0.09%), turnover (0.04%), and failure probability (0.06%).

On an aggregate basis, we find particularly the characteristics momentum strength (sixteen out of thirty-five countries), r-squared (fifteen out of thirty-five), age (thirteen out of thirty-five), book-to-market (thirteen out of thirty-five), as well as 52-week high price (thirteen out of thirty-five) to lead to statistically highly significant enhanced momentum returns

[10]This inference is drawn by the absolute number of characteristics yielding monthly positive enhanced returns with t-statistics greater than two.

(t-statistic greater than two).

In total, our results obtained from dependent double-sorting techniques provide first evidence for the ability of characteristics to function as momentum enhancers in a global data set. Our findings, however, also imply a high variability of the importance of characteristics across countries.

Overall, average returns obtained from double-sortings are highest for Belgium (0.92%), Australia (0.85%), Norway (0.80%), Canada (0.72%), and United Kingdom (0.71%). Average double-sorts within the U.S. amount to 0.46%. These findings are roughly consistent with returns obtained from classical momentum strategies which also tend to be highest for Australia (1.16%) and Belgium (1.15%). An exception remains Brazil, for which we obtain ordinary momentum returns of 1.19%, while average enhanced momentum returns within Brazil amount to 0.27%. Within the U.S., classical monthly momentum returns amount to comparable 0.34%. Accordingly, countries exhibiting lowest ordinary momentum returns are also among the ones with lowest average enhanced momentum returns (e.g. China).

2.4.2 Fama-MacBeth Regressions of Composite Momentum

Our baseline analyses start by testing which portion of actual momentum profits can be explained by predicted momentum. The rationale beyond is that if stock characteristics have no power in explaining momentum profits, their ability to forecast momentum profits should be close to zero, at least once controlling for idiosyncratic volatility and extreme past returns.

To interact ordinary momentum with predicted momentum, we run univariate Fama-MacBeth regressions of actual momentum profits on predicted momentum profit tertiles. As a next step, we control for actual momentum strength tertiles and IVOL tertiles (multivariate Fama-MacBeth regressions) to account for potential interdependencies highlighted by Bandarchuk and Hilscher (2013). Table 2.4 summarizes respective outcomes on a country-basis as well as for our internationally pooled data set.

Table 2.4: Fama-MacBeth Regressions on Predicted Momentum Profits

This table reports Fama-MacBeth regressions of actual momentum profits on predicted momentum profit tertiles only (univariate) as well as on predicted momentum profit tertiles, actual momentum strength tertiles, and actual IVOL tertiles (multivariate) on a country-basis as well as for our internationally pooled sample. The internationally pooled sample contains all countries apart from the U.S. market. Predicted momentum profits are calculated using country-specific predictors. For this purpose, each month for each country, we divide each of the eighteen characteristics into tertiles. For our internationally pooled sample, characteristics tertiles are calculated transnationally on a monthly basis. Each month for each country, we then run ordinary regressions of momentum profits on all eighteen characteristics tertiles simultaneously (multivariate). Then, on a five-year rolling basis, we apply average regression coefficients and constants for each of our eighteen characteristics tertiles and predict momentum profits for the next month solely upon the basis of our chosen set of characteristics. As a next step, we test how well our predicted momentum measure is in explaining actual momentum profits. That is, we run Fama-MacBeth regressions of actual momentum profits on predicted momentum profits tertiles (univariate) as well as on predicted momentum profits tertiles, actual momentum strength deciles, and actual IVOL tertiles (multivariate). For illustration purposes, all coefficients are multiplied by 100. The sample runs from M1:1989 to M6:2019. Respective t-statistics are indicated within parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

	Panel A: Univariate	Panel B: Multivariate		
Country	Predicted Mom	Predicted Mom	Mom-Str	IVOL
atl	0.8982***	0.7886***	0.2867***	0.0176
	(10.43)	(9.30)	(3.57)	(0.25)
bel	0.2655***	0.2243***	0.3887***	-0.0991
	(2.84)	(2.38)	(3.17)	(-0.94)
bra	0.3802**	0.3279**	0.2190	0.1457
	(2.40)	(2.17)	(1.33)	(1.01)
can	0.9835***	0.9066***	0.2268***	-0.0574
	(12.00)	(10.28)	(2.67)	(-0.78)
chi	0.1506	0.1374	0.2332*	0.0770
	(1.25)	(1.19)	(1.70)	(0.53)
chn	0.4013***	0.2561***	0.0655	0.1947***
	(4.07)	(3.12)	(0.78)	(3.47)
den	0.2944***	0.2297**	0.3696***	-0.0180
	(2.71)	(2.02)	(3.40)	(-0.17)
fin	0.0426	0.0278	0.0012	0.0026
	(0.41)	(0.27)	(0.01)	(0.03)
fra	0.3008***	0.2720***	0.2925***	-0.0187
	(3.46)	(4.30)	(3.40)	(-0.33)
ger	0.4847***	0.3480***	0.3391***	0.0187
	(4.34)	(4.08)	(3.83)	(0.27)
gre	0.6000**	0.5933***	0.3178	-0.1370
	(2.43)	(2.80)	(1.29)	(-0.81)
hkg	0.6435***	0.5957***	0.2260**	0.1087
	(5.84)	(5.42)	(2.02)	(1.23)
ido	0.3117	0.3805*	0.2693	-0.2013
	(1.36)	(1.66)	(1.41)	(-1.04)
ind	0.8491***	0.6812***	0.2483**	0.3076***
	(5.94)	(5.10)	(2.20)	(3.08)
ita	0.2885***	0.2273***	0.2602***	0.1148
	(3.62)	(3.15)	(2.93)	(1.38)
jap	0.2848***	0.2977***	0.0756	0.0272
	(4.78)	(5.32)	(1.13)	(0.82)

Table 2.4 (Cont'd): Fama-MacBeth Regressions on Predicted Momentum Profits

	Panel A: Univariate	Panel B: Multivariate		
Country	Predicted Mom	Predicted Mom	Mom-Str	IVOL
mal	0.5414***	0.4978***	0.1324	-0.0685
	(5.03)	(4.95)	(1.19)	(-0.90)
mex	0.3083**	0.2781**	0.3893**	-0.0665
	(2.26)	(2.14)	(2.63)	(-0.68)
net	0.3015***	0.2052**	0.3153***	0.0869
	(3.27)	(2.39)	(3.25)	(1.03)
nor	0.3421***	0.3250**	0.4592***	-0.0002
	(2.83)	(2.62)	(3.39)	(0.00)
nzl	0.4604***	0.4301***	0.3891***	0.0249
	(3.45)	(3.32)	(3.26)	(0.19)
pak	0.3536*	0.1070	0.6619***	0.1321
	(1.71)	(0.56)	(3.33)	(0.66)
phi	0.2229	0.1607	0.2479	0.0904
	(1.46)	(1.04)	(1.45)	(0.52)
pol	0.1409	0.0487	0.3015**	0.0068
	(0.73)	(0.34)	(1.99)	(0.05)
sin	0.5891***	0.5570***	0.1244	-0.0709
	(5.70)	(5.47)	(1.18)	(-0.84)
soa	0.2215**	0.2168**	0.3681***	0.0554
	(2.34)	(2.29)	(3.95)	(0.68)
sok	0.5133***	0.3799***	0.1754	0.0883
	(4.44)	(3.46)	(1.39)	(0.84)
spa	0.1603*	0.1490*	0.2498***	0.1104
	(1.76)	(1.65)	(2.67)	(1.47)
swe	0.5774***	0.5917***	0.2488**	-0.0576
	(5.67)	(6.19)	(2.52)	(-0.71)
swi	0.3094***	0.2830***	0.2026***	0.1053*
	(4.50)	(4.50)	(2.98)	(1.81)
tai	0.4190***	0.4072***	0.1796*	-0.0596
	(4.19)	(4.32)	(1.83)	(-0.77)
tha	0.1679	0.3067	-0.1079	0.0892
	(0.88)	(1.64)	(-0.59)	(0.61)
tur	0.3398***	0.3759***	0.4125***	0.0695
	(2.90)	(3.25)	(2.90)	(0.47)
uni	0.6692***	0.6369***	0.2469***	-0.0320
	(9.25)	(9.19)	(3.35)	(-0.58)
usa	0.4448***	0.4254***	0.1363*	0.0248
	(6.31)	(7.95)	(1.70)	(0.58)
internat	0.5185***	0.4863***	0.2270***	0.0050
	(13.36)	(12.55)	(5.88)	(0.16)

As shown in Table 2.4, our composite momentum predictor is statistically significant (t-statistics greater than two) in explaining actual momentum profits within 27 out of 35 countries.[11] Within 23 out of these 27 countries, we obtain statistical significance at the 1%-level. Countries for which we obtain statistical significance at the 1%-level comprise Australia, Belgium, Canada, China, Denmark, France, Germany, Hong Kong, India, Italy, Japan, Malaysia, Netherlands, Norway, New Zealand, Singapore, South Korea, Sweden, Switzerland, Taiwan, Turkey, United Kingdom as well as United States.

Specifically, t-statistics are highest for Canada (12.00), Australia (10.43), and United Kingdom (9.25). Within the U.S., t-statistics are still considerable 6.31. For our internationally pooled sample (comprising all of our chosen countries with the exception of the U.S.), t-statistics amount to 13.36. Respective regression coefficients range from highest 0.98 (Canada) to lowest 0.04 (Finland). For the U.S., we report a regression coefficient of 0.44, for our internationally pooled sample the respective coefficient equals 0.52.

Once controlling for idiosyncratic volatility and momentum strength, predicted momentum remains statistically significant (t-statistics greater than two) within all out of the reported 27 countries as well as within the international sample, with t-statistics and regression coefficients being only slightly reduced. Beyond, we find statistical significances of our predicted momentum measure to slightly increase when accounting for extreme past returns and firm-specific volatility within France, Greece, Japan, Sweden, Taiwan, Turkey, and the United States. We interpret these findings to provide empirical evidence for a systematic link between characteristics and momentum profits that is not explained by idiosyncratic volatility or extreme past returns.

2.4.3 Composite-Enhanced Trading Strategy

In this section, we study returns of portfolios formed using our composite-momentum metric. We apply 3x3 double-sorts using firm-specific predicted momentum and cumulative past returns. That is, within each predicted momentum tertile, we calculate ordinary momentum

[11] Within Chile, Finland, Indonesia, Pakistan, Philippines, Poland, Spain as well as Thailand, univariate regressions of actual momentum profits on predicted momentum yield t-statistics smaller than two.

strategies, then taking differences between ordinary momentum returns of highest/lowest predicted momentum tertiles (Q3-Q1). Ordinary momentum returns are again calculated going long (short) the tertile of past return winners (losers). Excluding the most recent month, we use a six months period to calculate past returns and establish the momentum portfolios. We apply dependent and equally-weighted sorting techniques. Most importantly, given the applied sorting technique, this investment strategy becomes neutral to ordinary momentum strategies. It is thus less likely "to be based on any kind of risk story" (Hong et al., 2000, p. 284).

Table 2.5 summarizes monthly long-short returns on a country-basis. Additionally, we report descriptive statistics (skewness, kurtosis, minimum returns) for monthly returns obtained from double-sorts on our predicted momentum measure and past returns. Lastly, we regress respective returns on Carhart's[12] (1997) four factors and report corresponding exposure with regard to the momentum factor (Winner-Minus-Loser; WML) and regression alphas.

As illustrated, highest country returns are obtained for Switzerland (1.29%), Germany (1.12%), Norway (1.12%), Brazil (1.10%), and Belgium (1.07%). Conversely, we report lowest statistically significant returns for France (0.64%), United Kingdom (0.72%), Taiwan (0.73%), and Japan (0.87%). For the U.S. market we obtain monthly portfolio returns of 0.88% (t-statistics: 3.13). For our internationally pooled sample, we obtain monthly excess returns of 1.14% (t-statistics of 5.27). As exemplified, for these countries our results do not indicate higher skewness, kurtosis or minimum returns for composite-enhanced momentum returns than for ordinary momentum returns reported in Table 2.1. Conversely, we for instance obtain insignificant results among others for countries such as China, South Korea or Malaysia as well as small European countries as for instance Denmark or Finland. Notably, these countries are also among the countries for which single characteristics-enhanced momentum strategies work least as illustrated within Table 2.3.

[12]The Carhart (1997) 4-factor model extends the Fama-French 3-factor model by adding an additional factor accounting for momentum returns (WML) besides the market, size, and value factors.

Table 2.5: Return- and Risk-Characteristics
of Predicted Momentum Strategies

This table reports descriptive statistics (average monthly returns, skewness, kurtosis, minimum returns) of returns obtained from dependent double-sorts on predicted momentum profits and past returns on a country-basis. Predicted momentum profits are calculated using country-specific predictors. For this purpose, each month for each country, we divide each of the eighteen characteristics into deciles. Each month, for each country we then run ordinary regressions of momentum profits on all eighteen characteristics tertiles simultaneously (multivariate). Then, on a five-year rolling basis, we apply average regression coefficients and constants for each of our eighteen characteristics tertiles and predict momentum profits for the next month solely upon the basis of our chosen set of characteristics. As a next step, we regress returns obtained from double-sorts on predicted momentum profits and past returns on Carhart's four factors (SMB, HML, WML, and MKTRF). We report respective regression constants. The sample runs from M1:1989 to M6:2019. Corresponding t-statistics are indicated within parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

	Ret Diff	Skew	Kurt	Min	Constant	WML Beta
atl	1.00%***	-0.13	4.58	-21.07%	0.00883**	0.21910***
	(3.13)				(2.55)	(3.52)
bel	1.07%**	1.05	7.92	-14.60%	0.01233**	0.11543
	(2.12)				(2.38)	(1.15)
bra	1.10%*	0.26	4.08	-23.40%	0.01089*	-0.15063
	(1.82)				(1.74)	(-1.49)
can	0.97%***	0.14	7.33	-28.61%	0.00895***	0.11476**
	(2.94)				(2.69)	(2.35)
chi	0.51%	0.50	4.27	-18.97%	-0.00019	0.46283***
	(1.06)				(-0.04)	(3.32)
chn	0.38%	-0.71	6.25	-20.46%	0.00610**	-0.09267
	(1.36)				(2.24)	(-1.39)
den	0.03%	-0.05	4.78	-29.92%	-0.00433	0.29526***
	(0.05)				(-0.74)	(2.93)
fin	-0.17%	0.17	3.37	-18.58%	-0.00156	0.04291
	(-0.35)				(-0.31)	(0.46)
fra	0.64%*	-0.37	8.70	-30.34%	0.00298	0.46750***
	(1.86)				(0.92)	(7.06)
ger	1.12%***	-0.62	7.11	-28.09%	0.00740**	0.48057***
	(3.09)				(2.34)	(8.75)
gre	0.66%	-2.06	15.28	-93.60%	0.00255	0.48606***
	(0.71)				(0.26)	(3.51)
hkg	0.36%	-1.93	13.00	-56.84%	0.00354	0.30600***
	(0.75)				(0.78)	(4.07)
ind	0.77%	-0.10	6.55	-33.42%	0.00110	0.44080***
	(1.51)				(0.25)	(6.29)
ido	0.17%	1.36	18.15	-52.61%	-0.00215	0.03147
	(0.18)				(-0.23)	(0.25)
ita	0.38%	-0.12	6.43	-31.96%	0.00166	0.37421***
	(0.98)				(0.45)	(5.06)
jap	0.87%***	-0.13	5.29	-18.91%	0.00804***	0.18611***
	(3.31)				(3.29)	(3.43)

**Table 2.5 (Cont'd):
Return- and Risk-Characteristics of
Predicted Momentum Strategies**

	Ret Diff	Skew	Kurt	Min	Constant	WML Beta
mal	0.09%	0.96	13.22	-23.44%	0.00141	-0.16234***
	(0.24)				(0.37)	(-2.70)
mex	0.68%	-1.40	13.13	-48.57%	0.00567	0.31770**
	(1.22)				(0.92)	(2.37)
net	1.02%**	0.28	5.13	-30.55%	0.00628*	0.51654***
	(2.43)				(1.64)	(7.98)
nor	1.12%*	0.01	4.22	-28.87%	0.00793	0.19403**
	(1.91)				(1.31)	(2.15)
nzl	0.87%	0.51	4.25	-14.68%	0.00029	0.52660***
	(1.41)				(0.05)	(4.10)
pak	0.02%	0.25	5.07	-42.96%	-0.00192	0.07590
	(0.03)				(-0.20)	(0.40)
phi	-0.74%	1.42	11.86	-25.61%	-0.00776	0.09833
	(-1.07)				(-1.09)	(0.84)
pol	-0.75%	-0.31	3.13	-22.32%	-0.00832	0.15925
	(-1.29)				(-1.39)	(1.32)
sin	0.37%	1.07	9.47	-24.75%	0.00457	0.14156*
	(0.84)				(1.00)	(1.76)
soa	0.41%	-0.25	4.60	-24.07%	-0.00123	0.27332***
	(0.96)				(-0.27)	(3.32)
sok	0.59%	-1.15	13.24	-64.53%	0.00035	0.3759***
	(1.12)				(0.07)	(5.08)
spa	0.61%	-0.29	4.42	-31.37%	0.00485	0.16988*
	(1.43)				(1.07)	(1.95)
swe	0.94%**	0.43	5.02	-24.85%	0.00814**	0.21280***
	(2.31)				(2.02)	(3.56)
swi	1.29%***	-0.44	6.31	-24.92%	0.01087***	0.46046***
	(4.16)				(3.87)	(8.32)
tai	0.73%*	-0.30	5.96	-22.15%	0.00631*	0.40631***
	(1.76)				(1.67)	(5.03)
tha	0.95%	-0.72	13.24	-72.00%	0.00796	0.27114***
	(1.42)				(1.16)	(2.83)
tur	0.85%	0.36	4.08	-25.75%	0.00761	-0.01000
	(1.50)				(1.30)	(-0.08)
uni	0.72%***	0.09	9.49	-26.23%	0.00593**	0.18600***
	(2.72)				(2.33)	(3.83)
usa	0.88%***	0.26	6.57	-20.60%	0.00988***	0.34823***
	(3.13)				(4.22)	(8.10)
internat	1.14%***	-0.01	5.25	15.51%	0.00902***	0.27152***
	(5.27)				(3.88)	(3.62)

Correlation between ordinary momentum returns reported in Table 2.1 and composite-enhanced momentum returns shown in Table 2.5 amount to 0.54 within the U.S. market, while we observe a high variability for international markets. Highest correlations between ordinary and composite-enhanced momentum returns across international markets are observed within France (0.60), India (0.53) and Switzerland (0.53) as well as Germany (0.50). Conversely, hardly any correlations between ordinary and composite-enhanced momentum returns are observed within countries such as Finland, Thailand, and Turkey. These findings are again in line with results reported in Section 2.4.1 indicating that single-characteristics enhanced strategies neither seem to work within these countries. Also, when regressing reported composite-enhanced momentum returns on Carhart's four factors, a considerable and mostly significant alpha remains within almost all of the markets exhibiting statistically significant composite-enhanced momentum returns. Beyond, we report a statistically significant WML beta in these markets, providing evidence on a common root cause for ordinary and composite-enhanced momentum returns.

Still, on an aggregate basis, we interpret results obtained from our out-of-sample tests as a systematic pattern between stock characteristics and composite-enhanced momentum returns that is not captured by either idiosyncratic volatility, momentum strength, or multi-factor asset pricing models to its full extent.

2.5 Cross-Country Analyses: Determinants of (Composite-Enhanced) Momentum Returns

2.5.1 Country Characteristics

What explains global differences of composite-momentum returns reported in Section 2.4? In this section, we apply cross-country analyses to empirically analyze which theoretical momentum explanation best fits reported findings. In accordance with theoretical explanations of ordinary momentum returns outlined in Section 2.2 and prior academic cross-country studies, we identify four sets of country characteristics. Detailed country variable descriptions are provided in Appendix A.2 of the Electronic Supplementary Material. In the following, we summarize applied country variables and justify the selection of each proxy.

Following prior studies as for instance Watanabe et al. (2013) or Docherty and Hurst (2018), the first group of country characteristics serves as proxies for market efficiency and trading frictions. These characteristics are applied to test for causes which are exclusively related to deviating national market environments. That is, they are applied to analyze whether reported differences in (composite-enhanced) momentum returns are not related to theoretical models of investor over- or underreaction but rather due to market inefficiencies and frictions.

We apply four measures to account for market efficiency and limits to arbitrage: DEV, MCAP, EFR, and SHORT. DEV serves as an indicator for developed markets based on Morgan Stanley Capital International (MSCI) classifications and has been applied in prior cross-country studies as for instance Watanabe et al. (2013). Given that multiple studies (as for instance Bekaert and Harvey (2002)) argue that market inefficiencies might be higher in non-developed markets, a corresponding dummy variable is included within cross-country analyses below. MCAP indicates a country's stock market capitalization to GDP and is taken from the World Bank Financial Development Database. Following the rationale provided by La Porta et al. (1997), higher ratios of market capitalizaiton of publicly listed companies to GDP imply more developed and efficient financial markets. The Overall Economic Freedom Ranking Scores (EFR) as a measure of restrictions to capital flows is taken from the Fraser Institute. Corresponding scores are available online at https://www.fraserinstitute.org/. Similar variables have been applied in prior academic studies as for instance by Chan et al. (2005). The rationale beyond is that capital controls might narrow foreign capital flows of sophisticated investors, thus serving as a limit to arbitraging away mispricings. The last proxy for market efficiency and limits to arbitrage is taken from Bris et al. (2007). SHORT is a measure that equals 0 if short-selling is prohibited within a country, 1 if short-selling is allowed. Within their study, Bris et al. (2007) find markets to be more efficient whenever short-selling is allowed and practiced. As within our study we apply long-short strategy returns, accounting for short-sale permissions is of specific importance.

Second, we account for cross-country cultural differences. To do so, we use the six cultural dimensions by Hofstede et al. (2010): INDIV, MASC, PD, UA, LTO, and INDUL. Individualism (INDIV) stands for the extent to which people feel independent as opposed to being integrated into groups (Collectivism). Members of individualistic cultures are assumed to rather look after themselves than others (Hofstede, 2011). Also, and as for instance argued by Chui et al. (2010), INDIV is related to investor overconfidence and self-attribution bias. If composite-enhanced momentum returns are found to be higher in high-individualistic countries, we thus infer the results to be empirical evidence for overreaction-based momentum explanations as for instance the one provided by Daniel et al. (1998). Long-Term Orientation (LTO) illustrates the degree to which a society agrees that the world is in permanent change, implying that preparation for the future is essentially and always needed. LTO is associated with values such as thrift and perseverance (Hofstede, 2011). Prior works as for instance the study by Docherty and Hurst (2018) imply that there exists a negative link between LTO and momentum.[13] If composite-enhanced momentum returns are found to be smaller in high LTO countries, we thus interpret our findings as empirical evidence for the rationale that composite-enhanced momentum is driven by myopic investors focusing on short-term price fluctuations rather than firm fundamentals (as argued by Docherty and Hurst (2018) for ordinary momentum returns). The remaining cultural dimensions of Hofstede et al. (2010) are applied as control variables. Masculinity (MASC) reflects the distribution of values between genders. That is, to which either masculine (assertive) or feminine (modest and caring) gender-specific values are pervasive within a society. Power Distance (PD) refers to the degree to which the less powerful accept unequally distributed power. Uncertainty Avoidance (UA) indicates the extent of a society's tolerance for uncertainty and ambiguity. That is, to what degree a society tries to avoid unknown and surprising situations. Finally, the sixth cultural dimension which has been incorporated post hoc by Hofstede et al. (2010), is Indulgence (INDUL). INDUL refers to the extent to which a society accepts relatively free gratification as opposed to suppressing natural impulses through strict social norms (Hofstede, 2011).

Third, to test for quality and speed of information diffusion, we apply the following prox-

[13] Please note that Docherty and Hurst (2018) report a positive link between investor myopia and momentum. Among others, they apply the inverse of the LTO variable by Hofstede (2001) to construct the myopia index. We therefore hypothesize a negative link between LTO and momentum.

ies: Earnings Management Score (EMS) to measure information quality; the Opacity Index (OPA) developed by Kurtzman et al. (2004) as a proxy for information opaqueness as well as the number of news articles (NEWS). Corresponding EMS values are obtained from Leuz et al. (2003). The rationale beyond inclusion of this proxy is that we hypothesize a fast diffusion of information whenever information quality tends to be high. For instance, the study by You and Zhang (2009) finds the diffusion speed to be slower in markets exhibiting lower levels of information readability. The logic behind inclusion of the variable OPA is that information uncertainty is assumed to be higher within high opaque market environments. Higher information uncertainty in turn implies that stock prices are less likely to fully reflect all available information immediately, with markets thus exhibiting slower speed of information diffusion. We therefore argue that a potentially positive link between OPA and composite-enhanced momentum returns should be considered as empirical evidence for the slow diffusion model by Hong and Stein (1999). NEWS indicates the number of news articles scaled by the number of firms per country. Corresponding data is taken from Griffin et al. (2011). We consider the number of news articles to be a good proxy for information production, assuming that more available information should either result in more efficient markets or in less efficient markets (given potential disparity in information or potential information overload).

Lastly, to account for the role of fund flows for composite-enhanced momentum, we additionally incorporate the following two variables: MFA and PFA. Both variables are taken from the World Bank Financial Development Database. MFA stands for a country's Mutual Fund Assets to GDP. Mutual funds are considered to be any type of collective investment scheme pooling many from multiple investors to acquire securities. In a similar vein, PFA indicates the ratio of a nation's pension fund assets to GDP.[14] Both variables are included to approximate the model by Vayanos and Woolley (2013). Vayanos and Woolley (2013) argue that momentum arises if (active) fund flows exhibit inertia and prices underreact to expected future flows. We thus hypothesize as follows: The higher the amount of investment funds within a country, the greater the amount of funds gradually outflowing an asset whenever a negative shock impacts the fundamental value of this asset. Following the model by Vayanos

[14] Corresponding variable definitions are taken from the World Bank Financial Development Database itself.

and Woolley (2013), we further argue that this depresses the corresponding asset price, thus leading to momentum which is our comprehension and justification beyond inclusion of the proxies MFA and PFA.

Table 2.6 summarizes reported country variables for our chosen set of thirty-five countries. With the exception of EFR, MFA, PFA, and MCAP, applied proxies are time-invariant. For averages of time-series variables, the sample period is from January 1989 to December 2017 due to international data availability issues.

As illustrated, our sample contains 19 developed markets (DEV=1) for which the EFR variable tends to be higher accordingly. MCAP ranges from lowest 19.40% (Pakistan) to highest 562.14% (Hong Kong). Short-selling is prohibited within seven out of thirty-five countries.

Lowest EMS values are reported for China (1.00), the U.S. (2.00), and South Africa (5.60), highest EMS values are shown for Greece (28.30), South Korea (26.80) as well as Italy (24.80). Information opaqueness tends to be highest in Indonesia (59), China (50) and the Philippines (50), whereas it is lowest in Finland (13), Denmark (19), Sweden (19), and United Kingdom (19). The number of news articles (NEWS) is greatest in the U.S. (183,749), India (57,404), and Spain (53,052). Lowest NEWS values are shown for Canada (2,178), Brazil (3,341), and United Kingdom (3,695).

Similarly, MFA is highest in developed markets. Within our sample, highest average MFA figures are reported for Singapore (408.47), Hong Kong (383.03), and Australia (73.21). Lowest MFA values are observed within the Philippines (1.16), Pakistan (1.38), and Turkey (2.43). Highest average PFA figures are reported for Netherlands (125.51), Switzerland (103.86), and the U.S. market (95.59), whereas lowest values occur within Pakistan (0.03), Greece (0.31), and China (0.85).

Table 2.6: Applied Country Characteristics

This table reports country characteristics of our chosen set of 35 countries. Listed characteristics are used in the cross-country analyses of enhanced momentum returns. Our chosen set of country characteristics proxies for market efficiency, limits to arbitrage, cultural difference, speed and quality of information diffusion as well as the role of fund flows. Detailed variable definitions and data sources are provided in Appendix A.2 of the Electronic Supplementary Material. The table contains the following cross-sectional characteristics: DEV, SHORT, EMS, OPA, NEWS, INDIV, MASC, PD, UA, INDUL, and LTO. The following proxies illustrate averages of time-series variables: EFR, MFA, PFA, and MCAP. For averages of time-series variables, the sample period is from January 1989 to December 2017. Proxies for market efficiency and limits to arbitrage comprise DEV, MCAP, EFR, and SHORT. Proxies for cultural differences include INDIV, MASC, PD, UA, INDUL, and LTO. EMS, OPA, and NEWS are applied to account for quality and speed of information diffusion. Lastly, to account for the role of (active) fund flows, we incorporate MFA and PFA.

Country	DEV	EFR	MFA	PFA	MCAP	SHORT	EMS	OPA	NEWS	INDIV	MASC	PD	UA	INDUL	LTO
atl	1	8.00	73.21	90.73	87.91	1	4.80	21	6155	90	61	38	51	71	21
bel	1	7.51	30.81	4.98	57.79	1	19.50	23	13163	75	54	65	94	57	82
bra	0	5.86	40.22	13.29	33.76	1		40	3341	38	49	69	76	59	44
can	1	8.08	44.48	63.80	114.53	1	5.30	23	2178	80	52	39	48	68	36
chi	0	7.63	10.39	50.66	87.94	1		29	10554	23	28	63	86	68	31
chn	0	5.99	8.09	0.85	36.86	0	1.00	50	31255	20	66	80	30	24	87
den	1	7.82	29.08	36.80	48.94	1	16.00	19	13198	74	16	18	23	70	35
fin	1	7.80	26.21	62.39	78.39	1	12.00	13	14064	63	26	33	59	57	38
fra	1	7.32	61.48	6.72	63.15	1	13.50	37	4685	71	43	68	86	48	63
ger	1	7.77	43.22	5.12	38.91	1	21.50	25	15878	67	66	35	65	40	83
gre	0	6.85	6.38	0.31	35.04	0	28.30	41	5496	35	57	60	112	50	45
hkg	1	8.91	383.03	29.74	562.14	1	19.50	20	22944	25	57	68	29	17	61
ido	0	6.53	4.50	1.89	27.04	0	18.30	59	4949	14	46	78	48	38	62
ind	0	6.38	6.35	1.57	48.34	1	19.10	48	57404	48	56	77	40	26	51
ita	1	7.25	18.22	4.97	30.54	1	24.80	43	34864	76	70	50	75	30	61
jap	1	7.77	27.86	26.45	77.66	1	20.50	28	7932	46	95	54	92	42	88
mal	0	6.90	22.98	51.64	144.96	0	14.80	35	21202	26	50	104	36	57	41
mex	0	6.57	6.89	8.86	26.84	1		44	8067	30	69	81	82	97	24
net	1	7.78	58.16	125.51	84.27	1	16.50	24	21702	80	14	38	53	68	67
nor	1	7.52	18.93	7.39	41.77	1	5.80		12163	69	8	31	50	55	35
nzl	1	8.32	15.27	17.14	36.64	1			13119	79	58	22	49	75	33
pak	0	5.77	1.38	0.03	19.40	0	17.80	45	7646	14	50	55	70	0	50
phi	0	6.93	1.16	3.53	52.75	1	8.80	50	6246	32	64	94	44	42	27
pol	0	6.67	3.72	9.67	21.12	1		41	17963	60	64	68	93	29	38
sin	1	8.57	408.47	36.56	175.01	0	21.60	24	23669	20	48	74	8	46	72
soa	0	6.65	30.91	89.07	184.75	1	5.60	34	11898	65	63	49	49	63	34
sok	0	7.27	8.60		77.69	0	26.80	37		18	39	60	85	29	100
spa	1	7.49	23.47	7.74	60.70	1	18.60	34	53052	51	42	57	86	44	48
swe	1	7.61	50.64	45.73	82.39	1	6.80	19	16667	71	5	31	29	78	53
swi	1	8.42	42.76	103.86	177.38	1	22.00	23	13225	68	70	34	58	66	74
tai	0	7.49				1	22.50	34	46700	17	45	58	69	49	93
tha	0	6.69	15.98	5.30	60.27	1	18.30	35	11760	20	34	64	64	45	32
tur	0	6.37	2.43	1.07	19.96	1		43	10822	37	45	66	85	49	46
uni	1	8.14	28.53	79.71	111.95	1	7.00	19	3695	89	66	35	35	69	51
usa	1	8.21	68.32	95.59	110.82	1	2.00	21	183749	91	62	40	46	68	26

2.5.2 Cross-Sectional Regressions

We strive to analyze causes of global differences in composite-enhanced momentum returns. Beyond, we aim to study whether drivers of composite-enhanced momentum returns deviate from drivers of ordinary momentum returns. In the regression analyses below, our dependent variable thus either constitutes the country-level ordinary momentum return or the country-level composite-enhanced momentum return. These momentum variables have two dimensions: country and time, thus exhibiting a panel data structure. Reported country characteristics as outlined in Section 2.5.1, in part exhibit a panel data structure. In part, however, they only exhibit the country-dimension, i.e. they are time-invariant. To account for this disparity in data structure, we apply averages of time-series country variables and exclusively apply cross-sectional regressions below. Due to international data availability issues of specific country variables, the sample period for cross-sectional regressions is limited from January 1989 to December 2017.

In doing so, we measure the between-effect (see e.g. Watanabe et al. (2013)). That is, we study drivers of differences in cross-country (composite-enhanced) momentum returns. Accordingly, the dependent variable is either the time-series average of country-specific ordinary momentum or the time-series average of country-specific composite-enhanced momentum return as outlined in Section 2.4.3. As independent variables we apply both, time-invariant and time-series averages of corresponding country characteristics described in Section 2.5.1.

Tables 2.7 to 2.9 summarize empirical findings for multiple cross-sectional regression specifications. Within each table, Panel A reports findings for cross-country differences in ordinary momentum returns. Panel B shows explanations with regard to cross-country differences in composite-enhanced momentum returns.

Table 2.7: Cross-Country Analyses:
Market Efficiency and Trading Frictions

This table summarizes empirical findings of cross-sectional regressions studying drivers of global differences for ordinary and composite-enhanced momentum returns. As dependent variable, we apply country-specific time-series averages of ordinary momentum returns (Panel A) as well as time-series averages of composite-enhanced momentum returns (Panel B). As independent variables, we apply our proxies for market efficiency and trading frictions. DEV is an indicator variable for developed markets. MCAP indicates the time-series average of a country's stock market capitalization to GDP. EFR stands for the time-series average of a country's economic freedom ranking score. SHORT is an indicator variable with regard to the allowance of short-selling. For illustration purposes, all coefficients are multiplied by 100. t-statistics are indicated within parentheses. The sample period runs from M1:1989 to M12:2017 due to availability of international country variables data. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A: Ordinary Momentum					
DEV	0.1360				-0.1356
	(1.05)				(-0.56)
MCAP		-0.0001			-0.0006
		(-0.14)			(-0.69)
EFR			0.0866		0.1390
			(1.01)		(0.80)
SHORT				0.3099**	0.3140*
				(2.01)	(1.77)
Intercept	0.5648***	0.6573***	-0.0054	0.3907***	-0.5068
	(5.93)	(7.21)	(-0.01)	(2.83)	(-0.44)
R^2	0.0325	0.0006	0.0298	0.1088	0.1435
Panel B: Composite-Enhanced Momentum					
DEV	0.3215**				0.4399
	(2.04)				(1.42)
MCAP		-0.0004			-0.0007
		(-0.44)			(-0.67)
EFR			0.1298		-0.0693
			(1.19)		(-0.31)
SHORT				0.2337	0.0592
				(1.14)	(0.26)
Intercept	0.4337***	0.6407 ***	-0.3565	0.4212**	0.8915
	(3.73)	(5.47)	(-0.44)	(2.31)	(0.61)
R^2	0.112	0.006	0.0412	0.0382	0.1546

Table 2.8: Cross-Country Analyses:
Cultural Dimensions

This table summarizes empirical findings of cross-sectional regressions studying drivers of global differences for ordinary and composite-enhanced momentum returns. As dependent variable, we apply country-specific time-series averages of ordinary momentum returns (Panel A) as well as time-series averages of composite-enhanced momentum returns (Panel B). As independent variables, we apply our proxies for cross-country cultural differences. These proxies comprise the six cultural dimensions by Hofstede: individualism (INDIV), masculinity (MASC), power distance (PD), uncertainty avoidance (UA), indulgence (INDUL), long-term orientation (LTO). For illustration purposes, all coefficients are multiplied by 100. t-statistics are indicated within parentheses. The sample period runs from M1:1989 to M12:2017 due to comparability reasons regarding remaining cross-sectional country regressions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Panel A: Ordinary Momentum							
INDIV	0.0069***						0.0050
	(2.99)						(1.34)
MASC		-0.0034					-0.0022
		(-1.00)					(-0.63)
PD			-0.0066**				-0.0014
			(-2.15)				(-0.31)
UA				0.0008			0.0023
				(0.28)			(0.90)
INDUL					0.0068**		0.0003
					(2.15)		(0.09)
LTO						-0.0072**	-0.0055*
						(-2.59)	(-1.76)
Intercept	0.2884**	0.8045***	1.0076***	0.5887***	0.2922*	1.0175***	0.7085
	(2.21)	(4.43)	(5.47)	(3.26)	(1.70)	(6.44)	(1.41)
R^2	0.2130	0.0304	0.1262	0.0024	0.1230	0.1689	0.3402
Panel B: Composite-Enhanced Momentum							
INDIV	0.0065**						-0.0001
	(2.09)						(-0.03)
MASC		-0.0007					0.0018
		(-0.15)					(0.43)
PD			-0.0104***				-0.0080
			(-2.75)				(-1.47)
UA				0.0026			0.0031
				(0.74)			(1.03)
INDUL					0.0097**		0.0116**
					(2.46)		(2.59)
LTO						0.0044	0.0085**
						(1.15)	(2.28)
Intercept	0.2783	0.6467***	1.1968***	0.4591**	0.1129	0.3779*	-0.2473
	(1.58)	(2.76)	(5.31)	(2.01)	(0.52)	(1.75)	(-0.41)
R^2	0.1166	0.0007	0.1907	0.0166	0.1551	0.0385	0.4231

Table 2.9: Cross-Country Analyses:
Information Quality and Diffusion Speed

This table summarizes empirical findings of cross-sectional regressions studying drivers of global differences for ordinary and composite-enhanced momentum returns. As dependent variable, we apply country-specific time-series averages of ordinary momentum returns (Panel A) as well as time-series averages of composite-enhanced momentum returns (Panel B). As independent variables, we apply our proxies for information quality and diffusion speed. The earnings management score (EMS) is a proxy for information quality. The opacity index (OPA) indicates the degree of information opaqueness. NEWS stands for the number of news articles scaled by the number of firms per country. For illustration purposes, all coefficients are multiplied by 100. *t*-statistics are indicated within parentheses. The sample period runs from M1:1989 to M12:2017 due to comparability reasons regarding remaining cross-sectional country regressions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

	Model 1	Model 2	Model 3	Model 4
Panel A: Ordinary Momentum				
EMS	-0.00126			0.00412
	(-0.14)			(0.45)
OPA		-0.0097*		-0.0131**
		(-1.70)		(-2.36)
NEWS			-0.0000	-0.0000
			(-1.28)	(-1.20)
Intercept	0.6160***	0.9338***	0.7038***	0.9922***
	(4.08)	(4.71)	(8.88)	(4.37)
R^2	0.0007	0.085	0.049	0.2309
Panel B: Composite-Enhanced Momentum				
EMS	0.0044			0.0122
	(0.38)			(0.98)
OPA		-0.0137*		-0.0147*
		(-1.87)		(-1.94)
NEWS			0.0000	0.0000
			(0.35)	(0.55)
Intercept	0.5658***	1.0345***	0.5837***	0.8564***
	(2.91)	(4.08)	(5.62)	(2.76)
R^2	0.0054	0.1016	0.0039	0.1641

Table 2.7 starts by summarizing findings when applying proxies for market efficiency and trading frictions. The results in Panel A show that ordinary momentum returns tend to be higher within countries that allow and practice short-selling (statistical significance at the 5%-level within univariate regression). When controlling for other proxies of market efficiency and trading frictions, the variable SHORT remains statistically significant (at the 10%-level) in explaining ordinary momentum returns. Additionally, the results imply that the proxies DEV, MCAP, and EFR have no explanatory power for ordinary momentum returns. Conversely, with regard to cross-country differences in composite-enhanced momentum returns (Panel B), DEV is the only proxy exhibiting (positive) explanatory power (at the 5%-level). In the multivariate regressions (where DEV, MCAP, EFR, and SHORT are applied jointly), however, the explanatory power of DEV for composite-enhanced momentum returns disappears.

We continue by analyzing the relation between (composite-enhanced) momentum and the six cultural dimensions by Hofstede et al. (2010). Table 2.8 summarizes corresponding results. The univariate regression results indicate that there exists a positive relationship between ordinary momentum returns and individualism (t-statics of 2.99). This finding is in line with prior research (Chui et al., 2010). Beyond, we find a positive link between ordinary momentum and indulgence (t-statistics of 2.15) and negative relations between ordinary momentum and power distance (t-statistic of -2.15) as well as negative relations between ordinary momentum and long-term orientation (t-statistics of -2.59). When applying multivariate regression analysis comprising the six dimensions simultaneously, the explanatory power of the proxies INDIV, INDUL, and PD for ordinary momentum disappears entirely. We attribute this pattern to potential multicollinearity issues.[15] Still, LTO remains significant even within multivariate regression analysis (t-statistic of -1.76). When applying average composite-enhanced momentum returns as dependent variable in univariate regressions (Panel B), we find that individualism (t-statistics of 2.09) and indulgence (t-statistics of 2.46) exhibit positive significance in explaining cross-country differences. Also, PD has negative significance in explaining composite-enhanced momentum returns within the uni-

[15] For instance, as shown in Appendix A.3 of the Electronic Supplementary Material, the correlation coefficient between INDIV and PD equals -0.72. Once excluding PD from the multivariate regression, INDIV again becomes statistically significant at the 5%-level.

variate regressions (t-statistics of -2.75). Beyond, multivariate regression results reveal that out of these proxies, indulgence is the only one to maintain its statistical significance. Opposed to this, INDIV and PD become insignificant in the multivariate regression. Again, this finding is to be considered with caution due to multicollinearity issues between the six cultural dimensions.

With regard to our proxies for information quality and diffusion speed, reported results in Table 2.9 imply a negative link between both, ordinary and composite-enhanced momentum returns and the opacity index. The EMS and NEWS variables are insignificant within the univariate regressions. When applying the three proxies jointly, we find the overall results to be unaffected. That is, multivariate regressions in both panels indicate a negative link between the dependent variable and the opacity index, whereas EMS and NEWS again have no explanatory power.

When applying univariate regressions for our proxies of fund flows (MFA, PFA), we obtain insignificant results for both, ordinary and composite-enhanced momentum returns. We therefore refrain from summarizing corresponding figures within this paper.

2.5.3 Competing Explanations of (Composite-Enhanced) Momentum

As of now, we exclusively have applied univariate regressions to test for the impact of each country characteristic upon both, ordinary and composite-enhanced momentum. Beyond, we have applied multivariate regressions for each group of country characteristics accordingly. As emphasized by Watanabe et al. (2013), a reasonable concern arising thereof is that potential correlations among applied (groups of) country characteristics might impact findings reported in Section 2.5.2.[16] Therefore, to test for the robustness of reported findings as well as to evaluate the relative importance of previously found significant proxies and thus potential momentum explanations, we proceed by applying multivariate regression analyses below.

Again, as dependent variables we apply the country-specific time-series average of ordinary

[16] Correlations of applied country characteristics are shown in Appendix A.3 of the Electronic Supplementary Material.

momentum returns or the country-specific time-series average of composite-enhanced momentum returns. As independent variables, we apply the proxies SHORT, INDIV, and OPA with regard to ordinary momentum. For composite-enhanced momentum, we account for DEV, INDIV, PD, and OPA. These proxies are chosen as they have shown highest statistical significance within univariate regressions. In the following analyses, following the approach by Watanabe et al. (2013), they are then paired with all other country characteristics, one at a time. As emphasized above, these steps are necessary to test for robustness and relative explanatory importance. In doing so, we simultaneously study which momentum model best fits our empirical findings.

Table 2.10 shows corresponding findings for ordinary momentum returns. Table 2.11 summarizes findings obtained for composite-enhanced momentum returns.

Most importantly, the results reported in Table 2.10 corroborate the robustness of the individualism proxy for ordinary momentum returns. Within each regression specification, INDIV remains relevant, at least at the 10% level. Conversely, the SHORT variable remains only significant within seven out of twelve regression specifications. Once applying INDIV and SHORT jointly, SHORT becomes insignificant whereas INDIV is relevant at the 5% level despite potential multicollinearity issues (correlation coefficient of 0.70). In a similar vein, the OPA variable remains relevant in explaining ordinary momentum returns within seven out of twelve regression specifications. Once applying OPA and INDIV jointly, OPA becomes insignificant whereas INDIV remains relevant at the 1%-level. Therefore, these findings emphasize that ordinary momentum returns tend to be higher in markets that practice short-selling, while simultaneously exhibiting less information opaqueness and above all higher degrees of investor overconfidence.

For composite-enhanced momentum returns, Table 2.11 shows that both, DEV, INDIV, and PD jointly are most significant in explaining global differences. The OPA variable remains negatively relevant in explaining composite-enhanced momentum returns within seven out of twelve regression specificiations.

Table 2.10: Cross-Country Analyses of Ordinary Momentum: Robustness Tests

This table shows results of cross-country regressions examining the effect of the previously found significant variables SHORT (Panel A), INDIV (Panel B), and OPA (Panel C) jointly with other measures of market efficiency, cultural differences as well as further measures of quality and speed of information diffusion. The dependent variable is the within-country time-series average of ordinary momentum returns. For illustration purposes, all coefficients are multiplied by 100. t-statistics are indicated within parentheses. *, **, and *** indicate statistical significance at the 10%, 5% as well as 1% level.

	Panel A: SHORT Against Alternatives											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
SHORT	0.28842*	0.3281**	0.2885*	0.08123	0.30149*	0.20266	0.30634*	0.20814	0.21235	0.28298*	0.21166	0.33007**
	(1.69)	(2.09)	(1.73)	(0.45)	(1.91)	(1.19)	(1.91)	(1.24)	(1.38)	(1.82)	(1.24)	(2.01)
DEV	0.04298											
	(0.31)											
MCAP		0.00020										
		(-0.29)										
EFR			0.03258									
			(0.37)									
INDIV				0.00612**								
				(2.11)								
MASC					-0.00317							
					(-0.96)							
PD						-0.00494						
						(-1.46)						
UA							0.00024					
							(0.09)					
INDUL								0.00496				
								(1.45)				
LTO									-0.00603**			
									(-2.08)			
EMS										0.00261		
										(0.30)		
OPA											-0.00659	
											(-1.06)	
NEWS												0.00000
												(-1.51)
INTERCEPT	0.38458***	0.4054***	0.16564	0.2623*	0.55204**	0.7513**	0.37717*	0.21768	0.78442***	0.34271	0.66451**	0.43942***
	(2.72)	(2.73)	(0.26)	(1.81)	(2.52)	(2.65)	(1.83)	(1.20)	(3.41)	(1.64)	(2.27)	(2.89)
R^2	0.1115	0.124	0.1125	0.2179	0.1327	0.1642	0.1071	0.1634	0.2153	0.1132	0.1294	0.1586

Table 2.10 (Cont'd)

	Panel B: INDIV Against Alternatives											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
INDIV	0.01033***	0.00671***	0.00741***	0.00612**	0.00679***	0.0062*	0.00699***	0.00568**	0.00573**	0.00863***	0.00583*	0.00773***
	(3.16)	(2.75)	(2.77)	(2.11)	(2.89)	(1.85)	(2.93)	(2.15)	(2.54)	(3.67)	(1.95)	(3.32)
DEV	-0.24181											
	(-1.46)											
MCAP		0.00005										
		(0.08)										
EFR			-0.03599									
			(-0.40)									
SHORT				0.08123								
				(0.45)								
MASC					-0.00313							
					(-1.01)							
PD						-0.00119						
						(-0.28)						
UA							0.00144					
							(0.58)					
INDUL								0.00318				
								(0.93)				
LTO									-0.00559**			
									(-2.09)			
EMS										0.01117		
										(1.38)		
OPA											-0.00214	
											(-0.32)	
NEWS												0.00383**
												(-2.06)
INTERCEPT	0.24396*	0.29573*	0.52918	0.2623*	0.44693**	0.38895	0.19485	0.18654	0.63962***	-0.02295	0.39699	0.32758**
	(1.85)	(1.90)	(0.86)	(1.81)	(2.18)	(1.03)	(0.93)	(1.09)	(3.06)	(-0.11)	(1.19)	(2.47)
R^2	0.2622	0.1961	0.2169	0.2179	0.2361	0.2129	0.2192	0.2338	0.3079	0.342	0.1879	0.2988

Table 2.10 (Cont'd)

	Panel C: OPA Against Alternatives											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
OPA	-0.01511*	-0.01168*	-0.01853*	-0.00659	-0.00214	-0.00922	-0.00577	-0.01125*	-0.00602	-0.00947*	-0.01292**	-0.01041*
	(-1.71)	(-1.82)	(-1.86)	(-1.06)	(-0.32)	(-1.51)	(-0.70)	(-1.87)	(-0.94)	(-1.77)	(-2.35)	(-1.81)
DEV	-0.15987											
	(-0.80)											
MCAP		-0.00057										
		(-0.74)										
EFR			-0.16143									
			(-1.08)									
SHORT				0.21166								
				(1.24)								
INDIV					0.00583*							
					(1.95)							
MASC						-0.00131						
						(-0.35)						
PD							-0.00333					
							(-0.70)					
UA								0.0026				
								(0.94)				
INDUL									0.00463			
									(1.27)			
LTO										-0.0065**		
										(-2.32)		
EMS											0.00489	
											(0.57)	
NEWS												0.00000
												(-1.42)
INTERCEPT	1.19286***	1.05917***	2.41689*	0.66451**	0.39699	0.97873***	0.99301***	0.8205***	0.57887*	1.27326***	0.91384***	1.02624***
	(3.14)	(4.12)	(1.74)	(2.27)	(1.19)	(3.96)	(4.47)	(3.52)	(1.69)	(5.38)	(4.39)	(4.93)
R^2	0.1042	0.1023	0.1193	0.1294	0.1879	0.0899	0.1011	0.113	0.1316	0.2239	0.1814	0.1417

Table 2.11: Cross-Country Analyses of Composite-Enhanced Momentum: Robustness Tests

This table shows results of cross-country regressions examining the effect of the previously found significant variables DEV (Panel A), INDIV (Panel B), PD (Panel C) and OPA (Panel D) jointly with other measures of market efficiency, cultural differences as well as further measures of quality and speed of information diffusion. The dependent variable is the within-country time-series average of composite-enhanced momentum returns. For illustration purposes, all coefficients are multiplied by 100. t-statistics are indicated within parentheses. *, **, and *** indicate statistical significance at the 10%, 5% as well as 1% level.

Panel A: DEV Against Alternatives												
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
DEV	0.38373**	0.44887*	0.29341*	0.17675	0.31833*	0.05036	0.38222**	0.23396	0.30735*	0.31688*	0.14327	0.33927**
	(2.29)	(1.72)	(1.68)	(0.77)	(1.92)	(0.23)	(2.29)	(1.49)	(1.94)	(1.83)	(0.56)	(2.05)
MCAP	-0.00093											
	(-1.04)											
EFR		-0.10688										
		(-0.62)										
SHORT			0.08704									
			(0.40)									
INDIV				0.00396								
				(0.88)								
MASC					-0.00007							
					(-0.02)							
PD						-0.00954*						
						(-1.81)						
UA							0.00473					
							(1.38)					
INDUL								0.00799**				
								(1.99)				
LTO									0.00377			
									(1.02)			
EMS										0.00723		
										(0.65)		
OPA											-0.00887	
											(-0.78)	
NEWS												0.00000
												(0.11)
INTERCEPT	0.47215***	1.15913	0.37926**	0.31073*	0.44028*	1.12142***	0.11516	0.07156	0.24377	0.32623	0.80224*	0.40891***
	(3.56)	(0.98)	(2.11)	(1.70)	(1.76)	(2.83)	(0.44)	(0.34)	(1.11)	(1.43)	(1.65)	(3.13)
R^2	0.1499	0.1224	0.1164	0.1327	0.1067	0.1922	0.1586	0.2097	0.1401	0.1186	0.1109	0.1225

Table 2.11 (Cont'd)

	Panel B: INDIV Against Alternatives											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
INDIV	0.00396	0.00691**	0.00605*	0.0066*	0.00667**	0.00167	0.00697**	0.00372	0.00785**	0.00974***	0.00373	0.00704**
	(0.88)	(2.11)	(1.67)	(1.69)	(2.09)	(0.39)	(2.20)	(1.07)	(2.54)	(3.04)	(0.93)	(2.12)
DEV	0.17675											
	(0.77)											
MCAP		-0.00025										
		(-0.28)										
EFR			0.02963									
			(0.24)									
SHORT				-0.01319								
				(-0.05)								
MASC					-0.00035							
					(-0.08)							
PD						-0.00891*						
						(-1.65)						
UA							0.00324					
							(0.98)					
INDUL								0.00732				
								(1.63)				
LTO									0.00665*			
									(1.82)			
EMS										0.01843*		
										(1.66)		
OPA											-0.00886	
											(-0.99)	
NEWS												0.00000
												(-0.03)
INTERCEPT	0.31073*	0.26853	0.07997	0.2825	0.29495	1.03013**	0.06669	0.04371	-0.13971	-0.15551	0.69092	0.24084
	(1.70)	(1.29)	(0.10)	(1.44)	(1.06)	(2.11)	(0.24)	(0.19)	(-0.49)	(-0.53)	(1.54)	(1.27)
R^2	0.1327	0.1308	0.1182	0.1166	0.1238	0.1946	0.1498	0.1843	0.1994	0.2663	0.127	0.1304

Table 2.11 (Cont'd)

	Panel C: PD Against Alternatives											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
PD	-0.00954*	-0.01034**	-0.01129**	-0.01015**	-0.00891*	-0.01113***	-0.01088***	-0.00791**	-0.01076***	-0.01115***	-0.00897	-0.01038***
	(-1.81)	(-2.65)	(-2.45)	(-2.40)	(-1.65)	(-2.79)	(-2.87)	(-2.00)	(-2.88)	(-2.84)	(-1.51)	(-2.66)
DEV	0.05036											
	(0.23)											
MCAP		-0.00020										
		(-0.23)										
EFR			-0.04473									
			(-0.36)									
SHORT				0.02742								
				(0.13)								
INDIV					0.00167							
					(0.39)							
MASC						0.00275						
						(0.65)						
UA							0.00364					
							(1.14)					
INDUL								0.00696*				
								(1.70)				
LTO									0.00498			
									(1.40)			
EMS										0.00836		
										(0.77)		
OPA											-0.0029	
											(-0.29)	
NEWS												0.00000
												(0.20)
INTERCEPT	1.12142***	1.20818***	1.58141	1.16207***	1.03013**	1.10364***	1.00522***	0.70384*	0.95481***	1.12397***	1.20643***	1.18098***
	(2.83)	(5.03)	(1.44)	(3.28)	(2.11)	(4.11)	(3.59)	(1.94)	(3.39)	(4.29)	(4.38)	(4.88)
R^2	0.1922	0.1928	0.1941	0.1912	0.1946	0.2018	0.2235	0.26	0.2391	0.2457	0.1666	0.1936

Table 2.11 (Cont'd)

	Panel D: OPA Against Alternatives											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
OPA	-0.00887	-0.01811**	-0.02246*	-0.01272	-0.00886	-0.01492*	-0.0029	-0.01654**	-0.00786	-0.01392*	-0.01485**	-0.01372*
	(-0.78)	(-2.22)	(-1.75)	(-1.57)	(-0.99)	(-1.92)	(-0.29)	(-2.19)	(-0.98)	(-1.94)	(-2.03)	(-1.81)
DEV	0.14327											
	(0.56)											
MCAP		-0.00121										
		(-1.24)										
EFR			-0.16045									
			(-0.83)									
SHORT				0.06628								
				(0.30)								
INDIV					0.00373							
					(0.93)							
MASC						0.00309						
						(0.64)						
PD							-0.00897					
							(-1.51)					
UA								0.00504				
								(1.45)				
INDUL									0.00732			
									(1.59)			
LTO										0.00570		
										(1.52)		
EMS											0.01136	
											(1.00)	
NEWS												0.00000
												(0.24)
INTERCEPT	0.80224*	1.28444***	2.50864	0.95013**	0.69092	0.92425***	1.20643***	0.82477***	0.47426	0.73706**	0.91042***	1.01417***
	(1.65)	(3.94)	(1.41)	(2.48)	(1.54)	(2.94)	(4.38)	(2.82)	(1.10)	(2.33)	(3.29)	(3.69)
R^2	0.1109	0.1477	0.122	0.1043	0.127	0.114	0.1666	0.1622	0.1714	0.1657	0.1542	0.1065

The fact that we observe a negative link between OPA and both, ordinary as well as composite-enhanced momentum returns, seems contradictory to the slow diffusion model by Hong and Stein (1999). In fact, our results indicate that markets which exhibit greater opaqueness exhibit less momentum returns. Simultaneously, this implies that ordinary and composite-enhanced momentum returns are higher whenever we observe markets with clear, accurate, and easily discernible information (as described by Kurtzman et al. (2004)).

When it comes to our proxies for market efficiency, we find within multivariate regressions that for ordinary momentum returns, the explanatory power of INDIV is stronger than the explanatory power of SHORT as well as all other proxies for market efficiency or trading frictions. For composite-enhanced momentum returns, we find that both, market efficiency and cultural variables matter strongly. Specifically, the DEV and PD proxies are highly relevant in explaining returns obtained from our composite-enhanced momentum strategy. Whereas INDIV also matters for composite-momentum, we find the t-statistics of PD to be stronger in most regression specifications. This finding implies that composite-enhanced momentum returns are highest within developed, highly individualistic markets whose citizens are unwillling to accept unequally distributed power.

A reasonable question arising thereof is how power distance itself relates to behavioral biases such as investor overconfidence and how this link in turn relates to theoretical models of momentum. As of now, we are not aware of studies explicitly focusing on the link between power distance and momentum returns. However, we would like to emphasize that reported findings are broadly related to a study by Ferris et al. (2013), indicating that power distance is inversely related to CEO overconfidence. Yet, we acknowledge that the link between CEO overconfidence and power distance deviates from a (potential) link between investor overconfidence and power distance which is still subject to be confirmed empirically.

Beyond, the results for both, ordinary and composite-enhanced momentum returns are consistent with the fact that markets with higher levels of investor overconfidence (INDIV) tend to be markets with lower levels of information opaqueness (OPA). Specifically, the correlation between INDIV and OPA amounts to -0.61 within our sample.

Overall, we thus cautiously interpret our findings as supportive evidence for overreaction-based explanations as for instance the one by Daniel et al. (1998) for both, ordinary and composite-enhanced momentun.

2.6 Conclusion

Empirical evidence is far from conclusive on what drives both, ordinary and characteristics-enhanced momentum returns. This study takes a composite look on how firm-specific characteristics relate to momentum profits across the globe. Specifically, we constructe a composite-momentum metric that combines information from a variety of stock characteristics. These characteristics have individually been shown to enhance momentum returns in prior work.

We demonstrate that momentum profits are predictable across many international markets when combining information given in multiple stock characteristics. Predicted momentum profits are comparatively simple to compute, can yield significant positive out-of-sample portfolio returns, and cannot be explained by idiosyncratic volatility, extreme past returns or Carhart's four factors to its full extent.

Cross-country analyses reveal that both, ordinary and composite-enhanced momentum returns tend to be positively correlated, higher within countries that exhibit less trading frictions (i.e. developed markets with no short-sale constraints) and markets that exhibit less information opaqueness. Simultaneously, we find composite-enhanced momentum returns to be higher in highly individualistic countries that simultaneously exhibit smaller degrees of power distance. We cautiously interpret our findings as empirical support for overreaction-based explanations of ordinary and composite-enhanced momentum.