The Remarkable Relevance of Characteristics for Momentum Profits

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Abstract

Inspired by Bandarchuk and Hilscher (2013), this paper is the first to provide a comprehensive analysis of a large set of momentum enhancing strategies for global equity markets. Our findings reveal the relevance of characteristics in enhancing and explaining momentum after accounting for possible interrelations with idiosyncratic volatility and extreme past returns. 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 price to matter for momentum profits. Overall, and consistent with behavioral explanation attempts, momentum appears to work best for hard-to-value firms with high information uncertainty. There are however substantial cross-country differences with regard to which characteristics truly enhance momentum. Our results imply that the link between idiosyncratic volatility, extreme past returns, and momentum profits itself is unable to comprehensively explain enhanced momentum returns and corroborate the heterogeneity of stock markets around the globe.

Keywords: momentum profits, stock characteristics, double-sorting, market efficiency, international stock markets

JEL Classification Codes: G12, G14

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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 Pontiff, 2016; Green et al., 2017; Jacobs and Müller, 2017). 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.

Taking insights obtained from the enhanced momentum literature to a higher-order logic, Bandarchuk and Hilscher (2013) are the first to provide a holistic explanation for why firm-specific attributes operate as momentum increasers. Within their study, they (2013, p. 809) argue that it is "not the characteristic screens per se that are responsible for elevated profits; rather, characteristic interaction patterns are the result of more extreme past return sorts." Accordingly, a link between extreme past returns, idiosyncratic stock return volatility, and momentum profits itself is assumed to explain momentum interaction patterns. This constitutes an unprecedented and profound explanation of enhanced momentum returns, implying a common channel across the whole characteristics universe. Simultaneously, according to Bandarchuk and Hilscher (2013), it substantiates a starting point for possible sources of ordinary momentum itself, and suggests that "explanations of the momentum anomaly that are based on evidence that characteristic screens enhance momentum profits should be reconsidered" (p. 810).

In the light of the importance of Bandarchuk and Hilscher (2013) to understand the sources of momentum profits, we re-evaluate their findings using a worldwide data set and a substantially larger set of return-enhancing characteristic drivers. The research questions we address are: Do stock characteristics have true power in enhancing and thus explaining momentum returns? Which characteristics are the most consistent drivers of momentum? Are there differences or commonalities across countries and regions worldwide? By true explanatory power, we refer to the ability of characteristics to enhance ordinary momentum profits after accounting for possible interrelations with idiosyncratic volatility and thus extreme past returns.

The conclusion drawn by Bandarchuk and Hilscher (2013) solely bases upon U.S. data. However, in many cases research results obtained for the U.S. market have proven not to hold (entirely) within international markets (Griffin et al., 2003; Chui et al., 2010; Jacobs and Müller, 2017). Due to the economic significance of international markets worldwide[1], we believe that novel insights and a holistic unterstanding of the momentum anomaly, specifically how stock characteristics relate to it, can best be achieved once conducting broad international out-of-sample tests.

We thus implement a 14 country-level analysis of 18 stock characteristics to test for their ability to truly enhance momentum. The countries which we include based on sufficient data availability are: Australia, Canada, France, Germany, Hong Kong, India, Italy, Japan, Malaysia, Korea, Switzerland, Taiwan, United Kingdom, and United States. The tested characteristics are based on a comprehensive review of the enhanced momentum literature

[1] According to the World Bank, international markets represent about 76% of the world's GDP in 2015 and about 60% of the total worldwide market capitalization at the end of 2015.

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.

Most strikingly, we find ubiquitous evidence on the relevance of characteristics in enhancing momentum returns. The explanatory power to a large extent maintains after accounting for idiosyncratic volatility and extreme past returns. This finding stands in contrast to the results of Bandarchuk and Hilscher (2013) and 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. The importance of these characteristics is generally 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). Our insights imply that a modest link between past returns, stock volatility, and momentum profits itself cannot explain enhanced momentum to its full extent.

Notwithstanding the overall success of the above mentioned momentum enhancers, our second main result is that there are substantial cross-country differences with regard to whether enhancing works in general and with regard to which characteristics are the strongest drivers. Overall, momentum enhancements are highly profitable in markets with higher ordinary momentum returns such as Europe or North America, but rarely work in Japan or Malaysia where ordinary momentum is also weak. This finding suggests a common root cause for ordinary and enhanced momentum which could be linked to cultural differences (Chui et al., 2010). Moreover, while some variation is to be expected, for many characteristics we find surprisingly large differences in return enhancing abilities across countries. For instance, an enhancement strategy based on *equity duration* yields a monthly return of 1.22% (t-statistic: 4.41) for the U.S. equity market, after controlling for momentum strength and idiosyncratic volatility. However, in most international markets the same strategy does not generate statistically significant returns.

To test if the link between momentum and stock characteristics is systematic and persistent, we strive to analyze out-of-sample whether momentum profits can be predicted upon the basis of our chosen set of characteristics. Specifically, we run rolling monthly regressions of momentum profits on characteristics (multivariate). By applying average regression coefficients and constants on a five-year rolling basis, we predict momentum profits for the following month. When running univariate Fama-MacBeth regressions, we find that our predicted momentum measure is statistically significant at the 1%-level in explaining actual momentum profits, within all of our countries investigated. Further, an investment strategy that double-sorts on predicted momentum and past returns delivers monthly returns of 1.63% for the U.S. market (t-statistic: 4.04) and 2.48% for our international sample (t-statistic: 6.23). 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.

Besides extending Bandarchuk and Hilscher (2013), 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 thus explaining momentum returns. This explanatory power to a large extent maintains after accounting for possible interrelations with idiosyncratic volatility and past returns. Moreover, the documented cross-country differences in return enhancing abilities may provide an interesting additional variation to test competing momentum theories in future work.

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., 2017). Specifically, by applying a (country, characteristics) 14x18 analysis, we conduct a broad international out-of-sample test and are able to detect which of our chosen characteristics are indeed major return 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), 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 (2017) also detect geographic stock market segmentations. Our findings reveal apparently striking evidence for regional patters between North America, Europe, Asia, and Australia. 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. This insight is also important for investors who can apply these findings to their investment strategies.

The paper proceeds as follows. Section 2 gives a brief overview of related literature and places our work within the current state of research on enhanced momentum strategies. In Section 3, we outline the data set underlying our analysis, our measurement of return dispersion, and our chosen set of characteristics. Section 4 reports our baseline results obtained from dependent double-sorting techniques and Fama-MacBeth regressions. Section 5 summarizes insights obtained from our study, discusses implications, and concludes.

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) as well as Vayanos and Woolley (2013) provide explanations complying with Fama's rational asset pricing paradigm.[2] Conversely, Barberis et al. (1998), Chan et al. (1996), Daniel et al. (1998), and Hong and Stein (1999) deliver plausible behavioral theories.[3]

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.

Contrarily, Chan et al. (1996) state that momentum results from a gradual diffusion of information into the market, particular 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. Contrarily to

[2] 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) as well as Daniel and Moskowitz (2016).

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

these underreaction-based behavioral explanations, 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.[4]

To test these competing explanations for the momentum effect empirically, numerous scholars have analyzed the ability of stock characteristics 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 risk"). Thus, to the extent this logic holds, conditioning on such firm-specific attributes should yield higher momentum returns.

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

[4]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.

[5]A non-exhaustive list on further momentum-enhancing characteristics 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), and maximum daily return (Jacobs et al., 2016).

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). Contrarily, studies conducted by Zhang (2006), Chui et al. (2010) as well as Hillert et al. (2014) 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.

To what extent (enhanced) momentum returns are indeed driven by irrational investor behavior – and if so which kind of irrationality – thus continues to be heavily debated.

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]

Our central interest lies in testing out-of-sample whether a modest link between idiosyncratic volatility, extreme past returns, and firm-specific attributes themselves is the sole driver of enhanced momentum returns. Beyond, we strive to contribute to our understanding of why momentum exists by documenting cross-country similarities and differences in the momentum enhancing effect.

3 Data and Methodology

3.1 Data Set

We derive our data set from Thomson Reuters 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 December 2015. The start 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.

Stocks that at the beginning of each month are contained within the lowest NYSE market capitalization decile are excluded from our study. 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 100 stocks to be available. If there are less than 200 months fulfilling the criteria of 100 stocks or above for a country, we exclude the respective country from our analysis. We justify this approach by the need of having sufficient observations to double-sort stocks into portfolios. Starting with 68 countries worldwide, our filtering criteria lead to a final sub-sample of fourteen countries. The final countries included are: Australia, Canada, France, Germany, Hong Kong, India, Italy, Japan, Malaysia, Korea, Switzerland,

[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.

Taiwan, United Kingdom, and United States.[7] Taken all countries together, our final sample contains a total of 39,480 stocks of which 11,145 can be ascribed to the U.S. market. Table I summarizes how firms (Panel A) and classical momentum profits (Panel B) are distributed among countries. Classical momentum profits are calculated going long the quintile of past return winners and short the quintile of past return losers. Excluding the most recent month, we use a six months period to calculate past returns and establish the momentum portfolios.

Insert Table 1

As shown in Table 1, our biggest countries are the U.S. (11,145 firms), Japan (4,778 firms), and Canada (3,869 firms). The smallest sub-samples include Switzerland (351 firms), Italy (480 firms), and Malaysia (1,139 firms). The worldwide percental market value (as of December 2015) accordingly is highest for the U.S. (37.13%), Japan (8.27%), and the United Kingdom (5.23%). Lowest percental market values are reported for Malaysia (0.60%), Italy (0.97%), and Taiwan (1.47%). Average median market value per month ranges from lowest 542.11 million USD (Malaysia) to highest 899.74 million USD (France).

Ordinary monthly momentum returns on average are highest for Australia (1.88%), Canada (1.42%), and the United Kingdom (1.37%) and lowest for Japan (-0.18%), Korea (0.29%), and Taiwan (0.41%). Respective standard deviations range from lowest 5.05% (Switzerland) to highest 8.90% (Korea). Within the U.S., ordinary momentum strategies yield average monthly returns of 0.60% with a standard deviation of 6.35%.

Overall, classical momentum returns tend to be negatively skewed, ranging from -6.34 (Malaysia) to -0.19 (Australia). Within France, Germany, and Italy, though, monthly momentum returns are even slightly positively skewed, ranging from 0.08 (Italy) to 0.58 (France). Annualized sharpe ratios are lowest for Japan (-0.12), Korea (0.11), and Taiwan (0.20) and highest for Australia (1.22), the United Kingdom (0.88), and Canada (0.84).

Our findings are in line with prior research, indicating that momentum strategies do not

[7] In total, these 14 countries represent 74.33% of the total market capitalization of the larger pool of all 68 countries by the end of 2015.

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). Similar to the U.S., we report declining momentum returns within Candada. Remaining international markets on average exhibit stable ordinary momentum returns throughout our investigated time period.

3.2 Measurement of Extreme Past Returns and Idiosyncratic Volatility

For reasons of simplicity and to ensure comparability, we calculate extreme past returns following 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:

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

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).

Idiosyncratic volatility is measured using regression residuals of ordinary monthly returns over the previous twelve months on the market factor (CAPM). Additionally, we calculate volatility ranks by dividing volatilities into twenty-five equally-sized portfolios (from lowest rank 1 to highest rank 25) each country-month. Depending on the respective portfolio, each stock is attributed a volatility rank (IVOL rank). 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.

3.3 Selection and Measurement of Momentum-Enhancing Characteristics

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 provides an overview of applied characteristics, their predicted way of interaction with momentum returns, respective reference studies as well as variable definitions.

Insert Table 2

As illustrated, we test 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 (Campbell et al., 2011), maximum daily return (Jacobs et al., 2016), equity duration (Dechow et al., 2004), 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). Ten out of our eighteen characteristics have also been applied by Bandarchuk and Hilscher (2013), namely: size, r-squared, turnover, age, analyst coverage, forecast dispersion, book-to-maket, price, illiquidity, and credit ratings. Due to a lack of international data availability, we apply failure probability as a distress measure to proxy the characteristic credit ratings applied by Bandarchuk and Hilscher (2013). Measurement details of our chosen set of characteristics follow the reference papers and are described in Table 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:[8]

$$char_{new} = (char_{ordinary} - median_{char}) \cdot sign(R_{t-6,t-1} - R_{median,t-6,t-1}) \tag{2}$$

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 and is necessary to conduct cross-sectional regressions of momentum profits on enhancing variables in the spirit of Bandarchuk and Hilscher (2013) as outlined further in section 4.3.

In line with respective reference studies in Table 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 quintile 5 and lowest in quintile 1, if our initial expectations are met.

3.4 Methodology

We apply common dependent double-sorts of characteristics and past returns for each country respectively. After having illustrated the ability of characteristics to function as momentum enhancers, we test in various ways whether elevated returns are driven by idiosyncratic volatility or momentum strength rather than characteristics themselves. Among others, we run monthly regressions of characteristic deciles on IVOL ranks and momentum strength deciles. Then, for each of the characteristics, we double-sort stocks into quintiles

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

according to respective characteristic residuals and past returns. If idiosyncratic volatility or momentum strength are the main drivers in enhancing momentum profits, sorting on residuals is assumed to remove or at least substantially reduce momentum returns.

Moreover, we apply Fama-MacBeth (1973) regressions of momentum profits on characteristics deciles only (univariate regressions) as well as on all characteristic deciles, momentum strength deciles, and idiosyncratic voltatility ranks (multivariate). Additionally, we test for the ability of our chosen set of characteristics to predict momentum profits. Specifically, we strive to analyze which portion of actual momentum profits can be explained by a predicted momentum measure that is calculated solely upon the basis of our chosen set of characteristics. Predicted momentum profits are calculated using regressions of actual realized momentum profits on all characteristic deciles on a rolling (monthly) basis. We also strive to test whether enhanced momentum returns can be further enhanced when double-sorting on our predicted momentum measure and cumulative past returns.

4 Empirical Results

4.1 Correlation Between Extreme Past Returns, Idiosyncratic Volatility, and Other Momentum-Enhancing Characteristics

Our study bases on the presumption that there exists a link between enhanced momentum, idiosyncratic volatility, and extreme past returns. In line with this reasoning, at the beginning, we show that more volatile stocks tend to have more extreme characteristics and thus that there indeed exists a link between stock returns and firm-specific attributes.

Each month for each country, we sort each stock characteristic, momentum strength, and idiosyncratic volatility into twenty-five portfolios (from lowest rank 1 to highest rank 25). With regard to size, r-squared, age[9], analyst coverage, book-to-market, price, information diffusion, and maximum daily return, stocks are sorted in descending order. We

[9] A difficulty we encounter concerning the characteristic *age* is the minor amount of distinct values and thus the problem of constructing equally-sized portfolios. In order to address this issue, we do not sort stocks into ranks and apply plain characteristic values unless otherwise stated.

then calculate correlation coefficients between stock characteristic ranks and IVOL ranks or momentum strength ranks respectively. Table 3 illustrates the relationship between extreme past returns and characteristics by summarizing the average of monthly rank correlations for each of the characteristics with idiosyncratic volatility and momentum strength. Also, we state the share of months for which correlation coefficients are significant at the 1% level. For reasons of brevity, we compare results obtained for the U.S. to an internationally pooled sample, containing all countries apart from the U.S. market. Characteristics, momentum strengths, and IVOL ranks are calculated on a country-basis.

Insert Table 3

As shown in Table 3, characteristics exhibiting highest and strongest correlations with idiosyncratic volatility (share significance of 100%) within the U.S. market are size, age, forecast dispersion, price, and equity duration. Notably, these characteristics are also among the ones displaying highest and strongest correlations with momentum strength. Within the internationally pooled data set, size, r-squared, age, forecast dispersion, failure probability, and revenue volatility are the ones having the highest and most significant rank correlation coefficients. Characteristics displaying lowest and weakest correlations with both, idiosyncratic volatility and momentum strength, within the U.S. and internationally pooled, are maximum daily return and costs of goods sold.

Overall, a consistent and highly significant link between idiosyncrativ volatility and characteristics, as well as momentum strength and characteristics cannot be neglected - for both, the U.S. and our internationally pooled data set.

Our findings are similar to the results reported by Bandarchuk and Hilscher (2013) who find strongest and most significant correlations for turnover, age, forecast dispersion, price, and credit rating (share significance of 100% for correlations with idiosyncratic volatility and higher than 90% for correlations with momentum strength).

4.2 Portfolio Returns of Momentum-Enhancing Trading Strategies

4.2.1 Results from Ordinary Double-Sorts

We continue 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. We do so by applying dependent and equally-weighted sorting techniques. In this section, we use “ordinary” double-sorts, which means we do not yet control for momentum strength and idiosyncratic volatility.

At the end of each month, for each country we sort each characteristic into quintiles. Within each characteristic quintile, we calculate ordinary momentum strategies. This means we go long the quintile of past return (t-6,t-1) winners and short the quintile of past return (t-6,t-1) losers (P5-P1). We then calculate the differences between momentum returns of highest and lowest characteristics quintiles. 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 quintile 5 (1).

Table 4 summarizes monthly returns obtained from ordinary double-sorts for each country-characteristic combination respectively. In the last two rows of the table we report average monthly returns obtained from double-sorting for each characteristic (with the exception of idiosyncratic volatility and momentum strength) and the number of characteristics exhibiting t-statistics greater than two.

Insert Table 4

As shown in Table 4, double-sorting on characteristics and past returns best functions within the United Kingdom, being followed by Australia, Canada, Germany, and the United States.[10] On the other hand, enhancing strategies hardly work within Asian countries. In

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

Japan, double-sorting on price and past returns even leads to a statistically significant monthly negative return of 1.09%. In European countries we find a strong segmentation. Whereas double-sortings perform well within Germany, Switzerland, and the United Kingdom, they hardly function within France and Italy. On the other side, our findings imply that turnover, price, and illiquidity are statistically insignificant within the United States.[11]

Highest returns on average are obtained when double-sorting on momentum strength (average monthly excess return of 1.38%), 52-week high price (1.22%), book-to-market (1.08%), and age (0.97%). In line with Bandarchuk and Hilscher (2013), idiosyncratic volatility also appears to be an important momentum enhancer with an average return of 0.95% per month across all countries. Lowest mean returns result from double-sorts on failure probability (-0.18%), price (-0.04,%), turnover (0.09%), and costs of goods sold (0.28%).

On an aggregate basis, we find particularly the characteristics size (with the exception of Asian countries), R^2 (seven out of fourteen countries), age (eight out of fourteen), book-to-market (nine out of fourteen), information diffusion (five out of fourteen), 52-week high price (six out of fourteen), and asset growth (five out of fourteen) to lead to statistically highly significant enhanced momentum returns (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. Size, for instance, only leads to statistically elevated momentum returns for approximately half of the countries investigated. Age delivers positive excess returns within all of the countries analyzed (even though not always statistically significant), with the exception of India for which it leads to monthly negative, however insignificant, returns of -0.07%. The discrepancy of the importance of analyst coverage is among the highest. Whereas double-sorting on this characteristic and past returns leads to high and statistically significant monthly excess returns in Australia, Canada, United Kingdom, and the U.S.

[11] We find results that coincide widely with the ones reported by Bandarchuk and Hilscher (2013). However, we also detect slight differences. In this regard, the most obvious possibility for reported deviations is the selection of different time periods (1989-2015 within our study as compared to 1964-2008 within Bandarchuk and Hilscher (2013)).

(thereby confirming findings in Hong et al. (2000)), it has either slightly positive or negative outcomes (insignificant) within all remaining countries.

Relatedly to existing literature stating that within Asian countries momentum strategies do not tend to perform well (Griffin et al., 2003; Chui et al., 2010), we find that the majority of characteristics does neither lead to statistically significant enhanced momentum returns. Few characteristics occassionally, though, seem to matter even within Asian countries. In Japan, for instance, age and book-to-market matter strongly. Within Malaysia, none of the characteristics applied with the exception of R^2 and book-to-market leads to highly statistically significant excess returns (i.e. t-statistics greater than two).

Average returns obtained from double-sorting (excluding double-sorts on idiosyncratic volatility and momentum strength) are highest for Australia (1.16%), Canada (0.98%), United Kingdom (0.98%), and Germany (0.87%). Average double-sorts within the U.S. amount to 0.60%. These findings are consistent with returns obtained from classical momentum strategies which are also highest for Australia (1.88%), Canada (1.42%), United Kingdom (1.37%), and Germany (1.20%). Within the U.S., classical monthly momentum returns amount to comparable 0.60%. Accordingly, countries exhibiting lowest ordinary momentum returns are also among the ones with lowest average enhanced momentum returns (Japan, Malaysia, Korea). Measured at country level, the correlation between ordinary momentum profits and average enhanced momentum returns is 73.31%, which may indicate that ordinary and enhanced momentum returns have the same underlying.

4.2.2 Results After Controlling for Extreme Past Returns and Idiosyncratic Volatility

As a next step, we test for the impact of extreme past returns and idiosyncratic volatility on the explanatory power of stock characteristics for momentum returns. For each country, we run monthly regressions for each of the characteristics deciles separately on momentum strength deciles as well as IVOL ranks. Following Fama-MacBeth (1973), we run following regressions on a rolling-basis:

$$char_{decile} = a + mom\_str_{decile} + IVOL_{rank25} + \varepsilon \qquad (3)$$

For each country-characteristic combination, we then sort stocks into quintiles according to residuals of the respective regression. If momentum strength or idiosyncratic volatility are the main drivers in enhancing momentum profits, sorting on residuals is assumed to substantially reduce excess returns. Table 5 summarizes average monthly momentum profits obtained from residual double-sorts for each country respectively.

Insert Table 5

When testing for how well enhanced returns are reduced once sorting on residual characteristics, we surprisingly find that a major part of characteristics still remains statistically relevant. In part, the explanatory power of characteristics is even increased.

Our results partly contradict Bandarchuk and Hilscher (2013) who find that the statistical significance of applied characteristics disappears, with the exception of age, forecast dispersion, and price. We confirm that age remains statistical relevant within the U.S. market. Forecast dispersion and price, however, become insignificant within our sample. Additionally, we find equity duration and revenue volatility (not tested by Bandarchuk and Hilscher (2013)) to maintain their explanatory power within the U.S. market.

Within Australia, six out of former nine characteristics remain relevant, within Canada five out of former nine. In Germany three out of former seven, in Taiwan three out of former six, within the United Kingdom eight out of former thirteen characteristics now exhibit t-statistics greater than two.

On an aggregate basis, we find size (three out of former five countries), r-squared (four out of former seven), age (six our of former eight), book-to-market (seven out of former nine), information diffusion (five out of former five), 52-week high price (three out of former six), and asset growth (five out of former five) to remain highly relevant in enhancing momentum returns. In part, the explanatory power of characteristics is even amplified once controlling for idiosyncratic volatility and momentum strength. This for instance pertains size within Switzerland or analyst coverage within Germany and Switzerland.

Overall, our findings suggest that momentum strength and idiosyncratic volatility, while being successful individual momentum enhancers, do not explain the bulk of enhanced momentum profits. The evidence is largely 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 and high asset growth) with high information uncertainty (low R^2), and when investors are prone to underreaction (information diffusion; nearness to 52-week highs and lows).

4.3 Sources of Momentum Profits: Evidence from Cross-Sectional Regressions

We proceed by further investigating the relationship between momentum profits and characteristics. To do so, we first run univariate Fama and MacBeth (1973) regressions of momentum profits on characteristic deciles.

To this end, we apply the methodology of Bandarchuk and Hilscher (2013). Specifically, momentum profits are measured 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):

$$R_{mom,t+1} = (R_{t+1} - R_{median,t+1}) \cdot sign(R_{t-6,t-1} - R_{median,t-6,t+1}) \tag{4}$$

By doing so, stocks exhibiting negative signs in both, past and forward periods, yield positive momentum profits. As stated, we run Fama-MacBeth regressions of momentum profits on characteristics deciles only (univariate). For this purpose, within each country, all mising values are replaced by (monthly) means.[12] At the end of each month, within each country, we then sort characteristics into deciles. For illustration purposes, all regression coefficients are multiplied by 100. Table 6 summarizes our results obtained from univariate Fama-MacBeth regressions.

Insert Table 6

As illustrated, the characteristics r-squared (nine out of fourteen), age (ten out of fourteen), book-to-market (fourteen out of fourteen), maximum daily return (eleven out of fourteen), and 52-week high price (eleven out of fourteen) have the highest explanatory power for momentum profits across all countries.[13]

Strongest dependencies are found between momentum profits and 52-week high price, book-to-market, and maximum daily return. For instance, a one standard deviation increase in 52-week high price decile implies an increase in momentum profits of 0.16% per month within the U.S., 0.83% per month within Australia, 0.81% within Canada, and 0.76% within Hong Kong. Similarly, a one standard deviation increase in book-to-market decile implies an increase in momentum profits of 0.42% per month within Canada, 0.23% within Germany and Japan, 0.35% within the United Kingdom, and 0.28% within the U.S. market. With regard to maximum daily return, a one standard deviation increase in the characteristic's decile implies a 0.61% increase in momentum profits per month within Australia, 0.78% within Canada, 0.40% within Germany, and 0.31% within the U.S. market. From a country-perspective, strongest relations between momentum profits and characteristics are on average found for Australia and Canada.[14] Overall, the regression results are largely

[12]We follow Green et al. (2017) who stress that in order to maintain as much characteristic information as possible, excluding missing observations would be counter-effective since least country-characteristic combinations exhibit full data. Likewise Green et al. (2017), we refer to Afifi and Elashoff (1966) who argue that when assuming multivariate normality of dependent and independent variables, the applied approach generates unbiased slope coefficient estimates.

[13]In many cases we detect opposing patterns for the closely related characteristics *price* and *size*. While this finding itself might seem surprising, it is in line with patterns reported by Bandarchuk and Hilscher (2013) for the U.S. market.

[14]Again, this inference is drawn by the absolute number of characteristics exhibiting t-statistics greater than two.

consistent with findings from our portfolio tests.

We proceed by running Fama-MacBeth regressions of momentum profits on all characteristics' deciles, momentum strength deciles, and IVOL ranks simultaneously (multivariate). We do so on a country-basis. Again, within each country all missing values of characteristics are replaced by (monthly) means before sorting into deciles. For illustration purposes, all regression coefficients are multiplied by 100.

Table 7 summarizes our results obtained from multivariate Fama-MacBeth regressions.

Insert Table 7

When running multivariate regressions of momentum profits on characteristics as well as momentum strength and idiosyncratic volatility, we find book-to-market (eight out of fourteen) as well as maximum daily return (eight out of fourteen) to matter the most, being followed by analyst coverage, illiquidity, information diffusion, and 52-week high price (all of which are important for three out of fourteen countries). Momentum strength plays a role in all non-Asian countries, with the exceptions of Korea (for which it matters) and Italy (for which it does not matter). Surprisingly, idiosyncratic volatility itself is only left statistically relevant in three countries.

4.4 Out-of-Sample Evidence Based on a Composite Momentum Enhancer

Are our insights obtained from preceding analyses random or rather systematically? Thus far, reported interaction patterns between momentum profits and stock characteristics are exclusively based upon in-sample calculations. We now proceed by testing out-of-sample whether a simultaneous consideration of several momentum-enhancers - beyond idiosyncratic volatility and momentum strength - leads to improved strategy returns. Are there economic gains for an implementable strategy with many enhancers? To the extent we find empirical results supporting our “enhanced-enhanced“ momentum strategy, we hypothesize a strong, hardly random, and systematic link between firm-specific attributes and momentum returns.

To do so, we calculate a predicted momentum measure solely upon the basis of our chosen set of characteristics. We then test 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.

In order to predict momentum profits, we run ordinary multivariate regressions of actual momentum profits on all characteristics deciles simultaneously, on a rolling monthly basis. At this point, it is necessary to emphasize that we exclusively apply our chosen set of stock characteristics. That is, we do not include idiosyncratic volatility or momentum strength to forecast momentum profits. 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. This procedure is similar to previous works (Lewellen, 2015; Green et al., 2017) that have applied Fama-MacBeth regressions in order to forecast stock returns by combining various firm characteristics.[15]

Next, we run univariate Fama-MacBeth regressions of actual momentum profits on predicted momentum profit deciles. As a next step, we control for actual momentum strength deciles and IVOL ranks (multivariate Fama-MacBeth regressions). If idiosyncratic volatility and momentum strength are the main drivers of (enhanced) momentum, we expect results to be substantially reduced once accounting for these variables. Table 8 summarizes respective outcomes on a country-basis as well as for our internationally pooled data set.

Insert Table 8

As shown in Table 8, within each of our countries as well as within the internationally pooled sample, our predicted momentum measure is statistically significant (at the 1%-level) in explaining actual realized momentum, with t-statistics being highest for the international data set (12.14), Canada (11.15), and Australia (10.75). Within the U.S., t-statistics are

[15] In this regard, Lewellen (2015) finds that forecasts based on firm characteristics have strong predictive power for actual stock returns; Green et al. (2017) find 12 out of former 94 characteristics to be reliable in independently forecasting stock returns while simultaneously stressing that in general, return predictability considerably declined in 2003.

still considerable 6.59. Lowest t-values are obtained for France (2.90), Korea (3.58), and Switzerland (3.90). Respective regression coefficients range from highest 0.33 (Canada) to lowest 0.09 (France). For the U.S., we report a regression coefficient of 0.14, for our internationally pooled sample the respective coefficient equals 0.22.

The estimated coefficients imply that a one standard deviation increase in predicted momentum profit decile equals an increase in actual momentum profits by 0.41% within the U.S. as well as by 0.63% within our internationally pooled sample.

Once controlling for idiosyncratic volatility and momentum strength, predicted momentum remains statistically significant within all of the countries applied as well as within the international sample, with t-statistics and regression coefficients being only slightly reduced. Within India, Japan, the United Kingdom, and the U.S., as well as for our internationally pooled sample, statistical significance even slightly increases. These findings again provide substantial empirical evidence for a systematic link between characteristics and momentum profits.

We continue by taking this logic to a higher level. That is, we proceed by double-sorting stocks on our predicted momentum measure and past returns. Again, we apply dependent and equally-weighted sorting techniques. Table 9 summarizes our findings for each country respectively as well as for the international sample.

Insert Table 9

As shown, double-sorting on our predicted momentum measure leads to statistically significant monthly returns for eleven out of fourteen countries as well as for our internationally pooled sample. Highest country returns are obtained within Germany (2.38%), Canada (2.25%), and Australia (2.01%). Conversely, we report lowest returns for Malaysia (0.39%), India (0.92%), and Switzerland (1.08%). Our internationally pooled sample yields monthly excess returns of 2.48% (t-statistic: 6.23). For the U.S. market, we report monthly returns of 1.63% (t-statistic: 4.04).

We continue by testing whether these “enhanced-enhanced“ momentum returns are due to possible crash risk as suggested in recent literature (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). To do so, we report descriptive statistics (skewness, kurtosis, minimum returns) for monthly returns obtained from double-sorts on our predicted momentum measure and past returns. Besides, we regress respective returns on Carhart's[16] (1997) four factors. Table 10 summarizes our findings.

Insert Table 10

As exemplified, our results do not indicate higher skewness, kurtosis or minimum returns for our "enhanced-enhanced" momentum returns than for ordinary momentum returns. Moreover, when regressing monthly excess returns on Carhart's four factors, a considerable and mostly significant alpha remains within the country-analysis as well as for our internationally pooled data set. Hence, our results do not support risk-based explanations for our "enhanced-enhanced" investment strategy.

On an aggregate basis, results obtained from our out-of-sample tests thus imply a systematic pattern between stock characteristics and (enhanced) momentum returns that is not explained by idiosyncratic volatility, momentum strength, possible crash risk or Carhart's four factors to its full extent.

5 Conclusion

This paper investigates the extent to which enhanced momentum returns are driven by a hidden double-sort on idiosyncratic volatility and thus extreme past returns as induced by Bandarchuk and Hilscher (2013). For this purpose, we rely on a set of fourteen countries and eighteen momentum-enhancing characteristics.

We provide novel insights into the debate by showing that there indeed exists a strong and robust link between firm-specific attributes, extreme past returns, and idiosyncratic volatility across countries worldwide. However, we report that this link is unable to explain

[16] 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.

enhanced momentum to its full extent. In particular, characteristics that reflect information uncertainty such as firm age, book-to-market, R^2, and characteristics that indicate investor underreaction such as information diffusion and 52-week high/low price are related to momentum profits after controlling for the two main influencers according to Bandarchuk and Hilscher (2013). We also document a strong correlation between ordinary and enhanced momentum profits at the country level. Overall, our findings are thus supportive for behavioral explanation attempts for momentum.

We are also able to illustrate that the explanatory power of characteristics varies substantially from country to country and region to region. Tests to enhance enhanced-momentum strategies by predicting momentum profits upon our chosen set of characteristics further suggest that these differences across global stock markets are persistent, cannot be explained by Carhart's four-factor model or possible crash risk, and could be exploited with simple trading strategies. The documentation of these international variations in enhanced-momentum profits is a new finding in the momentum literature, and suggests a new dimension to test underlying sources of momentum.

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Table 1: Summary Statistics

This table provides an overview of how firms (Panel A) and classical momentum profits (Panel B) are distributed among countries. Each month for each country we require at least 100 stocks to be available. If there are less than 200 months left having above 100 observations, respective nations are excluded from our analysis. Starting with 68 countries, our filtering criteria lead to a final sub-sample of fourteen nations. The countries included in our sample are: Australia, Canada, France, Germany, Hong Kong, India, Italy, Japan, Malaysia, Korea, Switzerland, Taiwan, United Kingdom, and United States. In Panel A, we report the total absolute number of anomaly 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 December 2015 as well as time-series averages of monthly median market values (reported in million USD). Within Panel B, we indicate summary statistics of classical momentum profits per country. We report mean, standard deviation, skewness, kurtosis, minimum, and sharpe ratio respectively. Classical momentum profits are calculated going long the quintile of past return winners and short the quintile 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. Our sample period runs from M1:1989 to M12:2015. Monthly returns are winsorized at the 0.01% and 99.9% levels. Stocks in the lowest market capitalization decile are excluded from the analysis. Months exhibiting below 100 stocks are excluded from the analysis as well.

Panel A: Sample Overview						
country	country abbrev.	total anomaly months	total # firms	average # firms per month	% market value	avg. median market value
Australia	atl	324	2,532	182.42	1.81%	640.70
Canada	can	324	3,869	276.77	1.99%	592.28
France	fra	324	1,481	240.68	3.29%	899.74
Germany	ger	324	1,381	247.05	2.85%	821.45
Hong Kong	hkg	267	1,522	233.84	3.60%	641.41
India	ind	280	2,746	226.20	2.61%	562.11
Italy	ita	324	480	130.60	0.97%	818.64
Japan	jap	324	4,778	1,350.59	8.27%	674.89
Malaysia	mal	283	1,139	135.98	0.60%	542.11
Korea	sok	307	2,286	199.03	2.05%	544.73
Switzerland	swi	324	351	120.02	2.47%	799.37
Taiwan	tai	247	2,052	269.84	1.47%	543.36
United Kingdom	uni	324	3,718	496.48	5.23%	781.29
United States	usa	324	11,145	2,374.65	37.13%	870.68
Panel B: Classical Momentum Returns						
country	mean	sd	skew	kurt	min	sharpe
atl	1.88%	5.33%	-0.19	4.77	-18.60%	1.22
can	1.42%	5.89%	-1.00	8.22	-33.44%	0.84
fra	0.97%	6.41%	0.58	17.40	-32.72%	0.52
ger	1.20%	5.99%	0.12	9.40	-27.89%	0.69
hkg	0.81%	7.16%	-1.33	8.38	-33.12%	0.39
ind	0.93%	7.32%	-1.18	10.12	-46.45%	0.44
ita	0.60%	5.75%	0.08	9.42	-24.84%	0.36
jap	-0.18%	5.29%	-0.62	8.97	-31.48%	-0.12
mal	0.65%	8.44%	-6.34	75.23	-100.42%	0.27
sok	0.29%	8.90%	-1.98	21.94	-77.73%	0.11
swi	1.03%	5.05%	-0.82	8.87	-26.21%	0.71
tai	0.41%	6.98%	-1.07	7.96	-37.47%	0.20
uni	1.37%	5.40%	-1.05	13.22	-36.81%	0.88
usa	0.60%	6.35%	-0.85	14.59	-37.37%	0.33

Table 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. We also indicate whether or not each respective characteristic has been applied by Bandarchuk and Hilscher (2013).

characteristic	abbrev.	sign	reference study	definition	BH
size	size	-	Hong et al. (2000)	market value of equity in USD	yes
r-squared	R^2	-	Hou et al. (2006)	fraction of a firms return variance explained by the market factor	yes
turnover	turn	+	Lee and Swaminathan (2000)	shares traded per month divided by the number of shares outstanding	yes
age	age	-	Zhang (2006)	number of years, based on a firm's first appearance in Datastream	yes
analyst coverage	nanalyst	-	Hong et al. (2000)	number of analysts covering stock	yes
forecast dispersion	eps-disp	+	Zhang (2006)	dispersion in forecasted EPS	yes
book-to-market	bm	-	Asness (1997)	book value of equity/market value of equity	yes
price	price	-	Bandarchuk and Hilscher (2013)	price index not adjusted for stock splits in US-Dollar	yes
illiquidity	illiquid	+	Amihud (2002)	average daily ratio of absolute stock return to dollar volume	yes
failure probability	failure	+	Campbell et al. (2011)	financial distress measure	yes*
capital gains	cgs	+	Grinblatt and Han (2005)	capital gains of stock over previous five years	no
information diffusion	ID	-	Da et al. (2014)	continuous information proxy/continuous information arrival	no
maximum daily return	max-ret	-	Jacobs et al. (2016)	a stock's maximum daily return over the past one month	no
equity duration	dur	+	Dechow et al. (2004)	average maturity of a stock's expected future cash flows	no
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	no
asset growth	ag	+	Cooper et al. (2008)	year-on-year percentage change in total assets	no
costs of goods sold	cogs	+	Sagi and Seasholes (2007)	costs of goods sold divided by a firms total assets	no
revenue volatility	rev-vola	+	Sagi and Seasholes (2007)	standard deviation of a stocks revenue growth throughout the past five years	no

*Due to lack of international data availability, we apply failure probability as a distress measure to proxy the characteristic credit ratings applied by B&H (2013).

Table 3: Correlation of Characteristics with IVOL and Momentum Strength

This table reports average monthly rank correlation coefficients of characteristics with idiosyncratic volatility (IVOL) and momentum strength (mom-str), for our internationally pooled data set and the U.S. market. The internationally pooled sample contains all countries apart from the U.S. market. Idiosyncratic volatility is calculated using regression residuals of monthly returns over the previous twelve months on the market factor (CAPM). Momentum strength is measured as the exponential difference of a stock's cumulative return over the past six months (t-6,t-1) and the median over the respective period, minus one. We indicate rank correlation coefficients and the share of months for which correlations are significant at the 1%-level (share significance). For this purpose, each month for each country we divide IVOL, momentum strength, and each of the eighteen characteristics into twenty-five equally-sized portfolios (ranks). With regard to size, r-squared, age*, analyst coverage, book-to-market, price, information diffusion, and maximum daily return, stocks are sorted in descending order. We then calculate monthly correlations for each of the characteristic ranks with respective IVOL ranks and momentum strength ranks. The sample runs from M1:1989 to M12:2015. Monthly returns are winsorized at the 0.01% and 99.9% levels. Stocks in the lowest market capitalization decile are excluded from the analysis. Months exhibiting below 100 stocks are excluded from the analysis as well.

	internat				usa			
	IVOL	share sig	mom-str	share sig	IVOL	share sig	mom-str	share sig
size	0.28	99.07%	0.09	82.41%	0.39	100.00%	0.16	93.52%
R^2	0.24	96.91%	0.08	79.94%	0.18	92.59%	0.08	77.47%
turn	0.16	84.57%	0.12	86.11%	0.26	98.77%	0.19	95.68%
age	0.19	98.46%	0.10	85.49%	0.36	100.00%	0.20	99.07%
nanalyst	0.16	88.89%	0.04	60.19%	0.19	97.53%	0.07	72.84%
eps-disp	0.18	99.69%	0.08	89.20%	0.34	100.00%	0.18	98.77%
bm	0.09	75.00%	0.08	75.93%	0.13	87.04%	0.11	77.47%
price	0.10	88.27%	0.02	40.74%	0.45	99.69%	0.18	95.68%
illiquid	0.13	91.98%	0.01	39.81%	0.23	94.75%	0.06	67.59%
cgs	0.03	47.53%	0.23	95.06%	0.04	54.01%	0.25	95.37%
id	-0.03	61.42%	0.11	85.80%	-0.04	65.74%	0.11	82.41%
failure	0.19	98.77%	0.06	72.22%	0.16	93.21%	0.10	72.84%
max-ret	-0.04	52.47%	0.01	59.26%	-0.06	66.98%	0.03	47.22%
dur	0.17	99.38%	0.09	89.81%	0.38	100.00%	0.20	98.46%
ag	0.05	55.86%	0.04	53.70%	0.12	91.67%	0.07	69.14%
P52-WH	0.03	58.64%	0.32	99.69%	0.07	72.53%	0.36	99.38%
cogs	0.01	31.17%	0.01	13.58%	-0.04	55.25%	-0.04	37.65%
rev-vola	0.20	97.22%	0.11	92.28%	0.35	99.07%	0.19	96.91%

*Due to lack of distinct values, age cannot be classified into twenty-five equally-sized portfolios in a variety of countries investigated. Thus, concerning age, we report ordinary correlations instead of rank correlations.

Table 4: 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 quintiles (with the exception of age for which we apply tertiles due to lack of distinct values). Within each characteristic quintile, we calculate ordinary momentum strategies. That is, we go long the quintile of past return (t-6,t-1) winners and short the quintile of past return (t-6,t-1) losers (P5-P1). We then calculate the differences between momentum returns of highest and the lowest characteristics quintiles. 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 (Q5-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-Q5). The sample runs from M1:1989 to M12:2015. Monthly returns are winsorized at the 0.01% and 99.9% levels. Stocks in the lowest market capitalization decile are excluded from the analysis. Months exhibiting below 100 stocks are excluded from the analysis as well.

	atl	can	fra	ger	hkg	ind	ita	jap	mal	sok	swi	tai	uni	usa	avg.
IVOL	1.95%	1.94%	0.74%	1.63%	0.10%	0.62%	0.90%	0.47%	-1.11%	0.56%	0.74%	1.22%	2.09%	1.39%	0.95%
	(2.91)	(3.58)	(1.42)	(3.43)	(0.14)	(0.87)	(1.60)	(1.66)	(-1.79)	(0.60)	(1.38)	(2.09)	(4.80)	(3.77)	
mom-str	2.70%	2.63%	1.15%	2.23%	0.78%	1.58%	1.15%	0.25%	-0.09%	-0.04%	1.95%	1.32%	2.53%	1.19%	1.38%
	(4.26)	(4.17)	(1.90)	(4.12)	(0.91)	(1.95)	(1.90)	(0.59)	(-0.12)	(-0.04)	(3.65)	(1.97)	(5.05)	(2.39)	
size	2.66%	1.67%	0.47%	1.02%	-0.08%	-0.28%	0.05%	-0.23%	0.05%	1.42%	0.94%	-0.03%	1.54%	0.53%	0.69%
	(4.90)	(3.42)	(1.08)	(2.13)	(-0.12)	(-0.37)	(0.09)	(-0.82)	(0.07)	(1.70)	(2.05)	(-0.06)	(4.21)	(1.82)	
R^2	2.09%	-0.08%	0.46%	0.45%	1.57%	0.36%	0.95%	0.50%	1.28%	-0.27%	1.62%	1.24%	1.73%	0.72%	0.90%
	(3.68)	(-0.17)	(0.93)	(0.91)	(1.89)	(0.54)	(1.82)	(2.00)	(2.00)	(-0.33)	(3.73)	(2.21)	(4.13)	(2.35)	
turn	-1.15%	-0.10%	0.71%	0.54%	0.58%	0.42%	1.18%	0.45%	-1.48%	-0.96%	0.02%	1.40%	-0.54%	0.16%	0.09%
	(-2.14)	(-0.18)	(1.28)	(1.16)	(0.65)	(0.54)	(2.08)	(1.59)	(-2.28)	(-1.06)	(0.05)	(2.38)	(-1.50)	(0.53)	
age	2.02%	1.07%	0.49%	1.87%	0.43%	-0.07%	0.14%	0.98%	0.96%	0.13%	1.29%	1.50%	1.39%	1.39%	0.97%
	(4.30)	(2.44)	(1.40)	(3.11)	(0.69)	(-0.13)	(0.29)	(2.20)	(1.76)	(0.19)	(2.69)	(2.86)	(3.01)	(4.19)	
nanalyst	2.29%	1.65%	0.07%	0.49%	-0.16%	0.29%	-0.10%	0.03%	-0.70%	0.03%	0.80%	-0.18%	1.87%	0.52%	0.49%
	(3.71)	(3.01)	(0.17)	(1.03)	(-0.20)	(0.43)	(-0.20)	(0.12)	(-1.03)	(0.05)	(1.66)	(-0.35)	(4.56)	(1.94)	
eps-disp	0.84%	1.52%	0.37%	0.00%	1.09%	-0.62%	0.61%	0.10%	-1.51%	0.95%	0.38%	-0.63%	0.98%	0.80%	0.35%
	(1.45)	(2.54)	(0.66)	(-0.01)	(1.34)	(-0.90)	(0.97)	(0.42)	(-2.02)	(1.03)	(0.73)	(-0.87)	(2.19)	(2.48)	
bm	0.42%	1.96%	0.91%	1.31%	0.37%	1.89%	1.52%	1.25%	1.47%	-0.38%	1.37%	1.08%	1.02%	0.88%	1.08%
	(0.60)	(3.19)	(1.67)	(2.50)	(0.47)	(2.36)	(2.85)	(4.04)	(2.31)	(-0.46)	(2.73)	(1.75)	(2.38)	(2.32)	
price	0.84%	1.29%	-0.43%	0.17%	0.21%	-1.81%	-0.17%	-1.09%	-0.53%	0.37%	0.98%	-1.75%	0.97%	0.43%	-0.04%
	(1.40)	(2.06)	(-0.75)	(0.33)	(0.26)	(-2.36)	(-0.32)	(-3.57)	(-0.72)	(0.50)	(1.85)	(-2.76)	(2.33)	(1.15)	
illiquid	2.44%	1.02%	0.78%	0.55%	1.02%	1.34%	-0.14%	0.17%	0.83%	0.04%	0.46%	-0.14%	1.75%	0.42%	0.75%
	(4.92)	(2.05)	(1.71)	(1.17)	(1.37)	(1.35)	(-0.25)	(0.61)	(1.30)	(0.05)	(0.98)	(-0.24)	(4.80)	(1.35)	
cgs	1.58%	1.10%	0.44%	2.24%	1.55%	2.48%	0.85%	-0.46%	0.29%	0.64%	0.26%	1.53%	1.39%	-0.29%	0.97%
	(2.50)	(1.63)	(0.64)	(4.25)	(1.61)	(2.80)	(1.15)	(-1.04)	(0.44)	(0.70)	(0.48)	(1.87)	(2.50)	(-0.46)	
ID	1.25%	1.39%	0.03%	1.31%	1.64%	1.44%	0.72%	0.10%	0.36%	0.60%	0.76%	1.73%	0.66%	0.44%	0.89%
	(2.20)	(2.61)	(0.05)	(2.69)	(2.29)	(1.84)	(1.28)	(0.32)	(0.46)	(0.72)	(1.45)	(2.63)	(1.54)	(1.07)	
failure	0.15%	0.59%	-0.02%	-0.31%	-0.52%	-1.11%	-0.16%	-0.65%	-1.15%	0.27%	0.45%	-0.34%	-0.56%	0.81%	-0.18%
	(0.25)	(0.93)	(-0.04)	(-0.60)	(-0.45)	(-1.35)	(-0.25)	(-2.40)	(-1.34)	(0.36)	(0.84)	(-0.49)	(-1.26)	(2.27)	
max-ret	1.04%	1.03%	2.13%	0.95%	1.01%	-0.03%	1.14%	1.24%	0.75%	0.84%	0.43%	-0.48%	-0.04%	1.13%	0.80%
	(1.67)	(1.74)	(3.32)	(1.67)	(1.01)	(-0.03)	(1.81)	(2.61)	(0.96)	(1.01)	(0.76)	(-0.73)	(-0.08)	(1.63)	
dur	0.67%	0.52%	0.93%	0.63%	0.17%	0.41%	0.34%	0.64%	-0.29%	1.28%	1.61%	-0.42%	1.50%	1.44%	0.67%
	(1.14)	(1.02)	(1.66)	(1.29)	(0.21)	(0.49)	(0.65)	(2.66)	(-0.45)	(1.76)	(3.50)	(-0.80)	(3.90)	(3.84)	
P52-WH	2.08%	1.32%	-0.33%	2.26%	3.05%	0.92%	0.69%	0.17%	1.22%	1.14%	0.39%	1.69%	2.16%	0.27%	1.22%
	(3.15)	(2.01)	(-0.42)	(3.29)	(2.95)	(1.03)	(0.93)	(0.29)	(1.55)	(1.06)	(0.59)	(2.07)	(3.67)	(0.37)	
ag	1.34%	0.82%	0.61%	1.25%	0.18%	-0.11%	-0.11%	1.31%	0.06%	0.29%	1.87%	0.75%	0.83%	0.41%	0.68%
	(2.40)	(1.58)	(1.20)	(2.87)	(0.24)	(-0.15)	(-0.20)	(5.51)	(0.09)	(0.36)	(3.93)	(1.15)	(2.30)	(1.69)	
cogs	-0.35%	-0.05%	0.13%	0.06%	1.24%	0.11%	-0.42%	-0.48%	0.71%	1.45%	0.38%	1.58%	-0.04%	-0.46%	0.28%
	(-0.61)	(-0.08)	(0.29)	(0.16)	(1.71)	(0.15)	(-0.66)	(-2.08)	(1.08)	(1.57)	(0.69)	(2.42)	(-0.10)	(-1.39)	
rev-vola	0.70%	0.88%	-0.22%	0.87%	0.19%	0.99%	0.27%	0.26%	-0.35%	-0.57%	0.71%	-0.33%	1.13%	1.25%	0.41%
	(1.14)	(1.47)	(-0.46)	(1.67)	(0.25)	(1.20)	(0.42)	(0.88)	(-0.48)	(-0.65)	(1.27)	(-0.48)	(2.50)	(3.37)	
avg.	1.28%	1.11%	0.47%	0.98%	0.72%	0.44%	0.47%	0.25%	0.04%	0.39%	0.87%	0.54%	1.12%	0.67%	0.67%
avg. without IVOL and mom-str	1.16%	0.98%	0.42%	0.87%	0.75%	0.37%	0.41%	0.24%	0.11%	0.40%	0.82%	0.46%	0.98%	0.60%	0.61%
# abs. value t-stat > 2	11	11	1	9	2	2	2	6	2	0	7	7	15	9	5.77

Table 5: Returns of Enhanced Momentum Strategies for Residual Characteristics

This table states average monthly returns obtained from double-sorting on residual characteristics and past returns (t-6,t-1). At the beginning, within each country all missing values of volatility, momentum strength, and characteristics are replaced by (monthly) means. Again, we measure momentum strength as the exponential difference of a stock's cumulative return over the past six months (t-6,t-1) and the median over the respective period, minus one. Then, by the end of each month within each country, we sort each characteristic as well as momentum strength into deciles. We also calculate volatility ranks (twenty-five portfolios of volatility). As a next step, we run rolling-regressions of characteristic deciles on volatility rank and momentum strength decile and compute quintiles of residual characteristics. Within each residual quintile, we calculate ordinary momentum strategies. That is, we go long the quintile of past return winners and short the quintile of past return losers (P5-P1). We then calculate differences between momentum returns of the highest and the lowest quintile. Again, for 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 (Q5-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-Q5). Corresponding t-statistics are indicated within parentheses. The sample runs from M1:1989 to M12:2015. Monthly returns are winsorized at the 0.01% and 99.9% levels. Stocks in the lowest market capitalization decile are excluded from the analysis. Months exhibiting below 100 stocks are excluded from the analysis as well.

	atl	can	fra	ger	hkg	ind	ita	jap	mal	sok	swi	tai	uni	usa	avg.
size	1.69%	1.48%	0.48%	0.60%	-0.26%	-0.44%	-0.01%	-0.14%	0.28%	0.73%	1.02%	0.23%	0.72%	0.05%	0.46%
	(3.43)	(2.97)	(1.25)	(1.32)	(-0.51)	(-0.70)	(-0.02)	(-0.52)	(0.37)	(0.64)	(2.27)	(0.43)	(1.95)	(0.19)	
R^2	0.85%	0.03%	0.84%	0.49%	1.23%	0.33%	0.36%	0.53%	1.50%	0.21%	1.17%	0.71%	1.14%	0.11%	0.68%
	(1.74)	(0.06)	(1.92)	(1.07)	(1.83)	(0.89)	(0.73)	(2.29)	(2.54)	(0.28)	(2.88)	(1.57)	(3.07)	(0.39)	
turn	-1.06%	0.03%	0.35%	-0.49%	-0.92%	0.75%	0.86%	0.12%	-0.26%	-0.21%	0.05%	0.93%	-0.61%	-0.24%	-0.05%
	(-1.98)	(0.06)	(0.72)	(-1.06)	(-1.06)	(0.89)	(1.51)	(0.50)	(-0.41)	(-0.24)	(0.09)	(1.69)	(-1.73)	(-0.92)	
age	1.02%	0.94%	0.62%	0.52%	-0.22%	1.72%	-0.02%	0.97%	0.65%	-0.75%	1.89%	1.02%	0.82%	0.47%	0.69%
	(2.26)	(2.02)	(1.40)	(1.06)	(-0.23)	(2.60)	(-0.03)	(3.25)	(1.00)	(-0.90)	(3.61)	(1.60)	(2.35)	(1.69)	
nanalyst	1.64%	0.93%	0.10%	0.81%	0.08%	0.65%	-0.44%	0.05%	-0.17%	-0.16%	0.87%	-0.12%	1.22%	0.26%	0.41%
	(3.54)	(1.84)	(0.25)	(1.77)	(0.10)	(1.01)	(-1.00)	(0.22)	(-0.18)	(-0.07)	(1.81)	(-0.24)	(3.01)	(0.88)	
eps-disp	0.17%	0.68%	0.17%	-0.74%	-0.09%	-0.82%	-0.18%	-0.10%	-1.15%	-0.05%	-0.36%	-0.44%	0.72%	0.23%	-0.14%
	(0.30)	(1.36)	(0.40)	(-1.85)	(-0.15)	(-1.37)	(-0.37)	(-0.32)	(-1.66)	(-0.11)	(-0.83)	(-0.95)	(1.93)	(0.91)	
bm	0.17%	1.23%	0.71%	0.63%	0.50%	1.66%	0.46%	1.09%	1.47%	-0.27%	1.17%	1.80%	1.16%	0.57%	0.88%
	(0.25)	(2.06)	(1.42)	(1.24)	(0.63)	(2.12)	(0.94)	(3.73)	(2.36)	(-0.36)	(2.40)	(3.03)	(2.78)	(1.59)	
price	0.75%	0.89%	-0.32%	-0.19%	-0.57%	-2.23%	0.12%	-1.11%	-0.98%	0.04%	0.92%	-2.25%	0.24%	-0.26%	-0.35%
	(1.46)	(1.67)	(-0.65)	(-0.40)	(-0.72)	(-2.53)	(0.23)	(-3.46)	(-1.55)	(-0.01)	(1.81)	(-3.58)	(0.70)	(-0.70)	
illiquid	1.43%	0.65%	0.11%	0.52%	0.15%	1.18%	0.12%	0.20%	1.32%	-0.22%	0.28%	0.57%	0.75%	0.35%	0.53%
	(3.30)	(1.25)	(0.27)	(1.23)	(0.19)	(1.44)	(0.25)	(0.79)	(2.02)	(-0.51)	(0.63)	(0.90)	(2.09)	(1.23)	
cgs	0.45%	0.12%	-0.23%	1.33%	1.22%	1.70%	0.29%	-0.02%	0.04%	0.37%	-0.31%	0.99%	0.01%	-0.44%	0.39%
	(0.75)	(0.20)	(-0.44)	(2.89)	(1.25)	(1.96)	(0.54)	(-0.04)	(0.08)	(0.55)	(-0.62)	(1.36)	(0.02)	(-0.93)	
ID	1.05%	1.45%	0.03%	0.89%	1.64%	0.88%	0.67%	0.16%	0.14%	0.71%	0.43%	1.45%	0.26%	0.26%	0.72%
	(2.06)	(2.64)	(0.07)	(2.10)	(2.44)	(1.16)	(1.40)	(0.51)	(0.23)	(0.90)	(0.95)	(2.41)	(0.66)	(0.68)	
failure	-0.14%	0.61%	0.05%	-0.64%	-0.79%	-2.10%	-0.44%	-0.82%	-0.76%	-0.38%	0.45%	-0.10%	-0.54%	0.11%	-0.39%
	(-0.29)	(1.10)	(0.10)	(-1.40)	(-1.10)	(-2.68)	(-0.91)	(-2.70)	(-1.20)	(-0.53)	(1.05)	(-0.17)	(-1.28)	(0.46)	
max-ret	0.48%	0.93%	1.92%	0.91%	1.29%	0.52%	1.12%	1.27%	0.41%	1.09%	0.50%	0.23%	0.07%	1.13%	0.85%
	(0.78)	(1.62)	(3.21)	(1.62)	(1.40)	(0.59)	(1.97)	(2.85)	(0.49)	(1.31)	(0.94)	(0.37)	(0.13)	(1.77)	
dur	0.24%	-0.22%	0.82%	0.05%	0.70%	0.16%	-0.01%	0.42%	-1.11%	0.16%	1.17%	-0.37%	0.73%	1.22%	0.28%
	(0.44)	(-0.46)	(1.85)	(0.11)	(1.01)	(0.36)	(-0.01)	(1.87)	(-1.91)	(0.23)	(2.72)	(-0.71)	(2.08)	(4.41)	
P52-WH	1.33%	1.22%	-1.47%	0.89%	2.15%	1.38%	0.21%	0.06%	1.08%	0.81%	0.51%	1.55%	1.46%	-0.10%	0.79%
	(2.23)	(1.90)	(-2.10)	(1.40)	(2.11)	(1.68)	(0.30)	(0.10)	(1.44)	(0.93)	(0.87)	(1.84)	(2.87)	(-0.14)	
ag	1.10%	1.08%	0.50%	1.11%	-0.04%	0.33%	-0.34%	1.31%	0.07%	-0.19%	1.22%	0.89%	0.95%	0.15%	0.58%
	(1.92)	(2.17)	(1.10)	(2.56)	(-0.05)	(0.48)	(-0.63)	(5.62)	(0.11)	(-0.24)	(2.59)	(1.55)	(2.78)	(0.58)	
cogs	0.12%	0.26%	-0.12%	-0.09%	1.33%	0.23%	-0.44%	-0.39%	0.74%	1.22%	-0.17%	1.29%	0.02%	-0.30%	0.26%
	(0.24)	(0.50)	(-0.28)	(-0.24)	(1.74)	(0.33)	(-0.84)	(-1.80)	(1.21)	(1.42)	(-0.35)	(2.22)	(0.05)	(-1.06)	
rev-vola	0.55%	-0.14%	0.35%	0.79%	-0.27%	1.09%	0.23%	-0.09%	0.37%	0.37%	0.87%	-0.11%	0.53%	0.75%	0.38%
	(1.39)	(-0.22)	(0.57)	(1.42)	(-0.42)	(1.83)	(0.29)	(-0.63)	(0.62)	(0.49)	(1.69)	(-0.24)	(1.83)	(3.74)	
avg.	0.66%	0.68%	0.27%	0.41%	0.40%	0.39%	0.14%	0.19%	0.20%	0.19%	0.65%	0.46%	0.54%	0.24%	0.39%
# abs. value t-stat > 2	6	5	1	3	2	2	0	5	3	0	6	3	8	2	3.29

Table 6: Fama-MacBeth Regressions Univariate

We run Fama-MacBeth regressions of momentum profits on characteristics deciles only (univariate). For this purpose, within each country, all missing values of characteristics are replaced by (monthly) means. At the end of each month, within each country, we then sort characteristics into deciles. With regard to size, r-squared, age, analyst coverage, book-to-market, price, information diffusion, and maximum daily return, deciles are ranked in descending order. Momentum profits are measured as a stock's forward return (t+1) 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 (1) or a loser (-1). Winner stocks are stocks having above-median past returns. Loser stocks are stocks having below-median past returns. Past returns are calculated using cumulative returns per firm over the previous six months (t-6,t-1). For illustration purposes, all regression coefficients are multiplied by 100. Corresponding t-statistics are indicated within parentheses. Significance levels are shown as follows: * displays significance at the 10% level, ** significance at the 5% level and *** significance at the 1% level. The sample runs from M1:1989 to M12:2015. Monthly returns are winsorized at the 0.01% and 99.9% levels. Stocks in the lowest market capitalization decile are excluded from the analysis. Months exhibiting below 100 stocks are excluded from the analysis as well.

	atl	can	fra	ger	hkg	ind	ita	jap	mal	sok	swi	tai	uni	usa	avg.
IVOL	0.031	0.022	0.023	0.056***	0.076**	0.124***	0.053**	0.037***	0.053**	0.088**	0.062***	0.066**	0.029	0.045**	0.066
	(1.31)	(0.88)	(0.99)	(2.82)	(2.42)	(3.72)	(2.17)	(3.08)	(2.16)	(2.49)	(2.99)	(2.44)	(1.50)	(2.27)	
mom-str	0.195***	0.160***	0.102***	0.114***	0.123***	0.149***	0.087***	0.021	0.124***	0.093**	0.098***	0.098***	0.135***	0.072**	0.119
	(7.45)	(6.48)	(3.15)	(4.03)	(3.63)	(3.85)	(3.00)	(0.98)	(3.81)	(2.09)	(4.09)	(2.98)	(5.74)	(2.56)	
size	0.049***	0.042**	0.032**	0.018	0.004	-0.004	0.013	-0.021*	-0.007	0.052*	0.023	-0.026	0.041***	0.007	0.016
	(2.59)	(2.27)	(2.01)	(1.00)	(0.16)	(-0.12)	(0.69)	(-1.85)	(-0.24)	(1.65)	(1.50)	(-1.19)	(2.85)	(0.73)	
R^2	0.045**	0.013	0.042**	0.038*	0.086***	0.059**	0.066***	0.012	0.036	-0.016	0.0573***	0.051**	0.082***	0.019	0.042
	(2.48)	(0.71)	(2.06)	(1.95)	(2.75)	(2.19)	(3.68)	(1.18)	(1.57)	(-0.50)	(3.10)	(2.55)	(5.74)	(1.41)	
turn	-0.047***	0.030	0.016	0.011	0.080***	0.062**	0.025	0.030**	0.057**	0.044	0.022	0.106***	-0.043***	0.039***	0.031
	(-2.76)	(1.57)	(0.68)	(0.57)	(2.74)	(2.25)	(1.18)	(2.07)	(2.20)	(1.61)	(1.28)	(3.80)	(-3.47)	(2.70)	
age	0.061***	0.049***	0.067***	0.045**	0.021	0.075**	0.062***	0.035***	0.001	-0.018	0.069***	0.033	0.060***	0.052***	0.044
	(4.07)	(3.38)	(3.69)	(2.31)	(0.88)	(2.34)	(3.64)	(3.35)	(0.03)	(-0.76)	(4.63)	(1.32)	(4.90)	(4.83)	
nanalyst	0.095***	0.081***	0.055***	0.033	0.060*	0.157***	0.029	-0.003	-0.020	0.066	0.044**	0.022	0.088***	0.032***	0.053
	(4.98)	(4.36)	(2.98)	(1.38)	(1.93)	(2.67)	(1.65)	(-0.18)	(-0.71)	(1.58)	(2.58)	(0.80)	(5.39)	(2.87)	
eps-disp	-0.003	-0.027	-0.030	-0.017	-0.006	-0.056*	-0.056***	-0.018*	-0.066***	0.011	-0.015	-0.053**	-0.013	-0.009	-0.026
	(-0.14)	(-1.09)	(-1.31)	(-0.70)	(-0.24)	(-1.75)	(-2.64)	(-1.66)	(-2.86)	(0.29)	(-0.77)	(-2.12)	(-0.80)	(-0.64)	
bm	0.109***	0.146***	0.100***	0.081***	0.117***	0.176***	0.112***	0.081***	0.069***	0.067**	0.105***	0.140***	0.120***	0.098***	0.109
	(4.65)	(5.82)	(3.89)	(3.92)	(3.80)	(5.10)	(5.59)	(6.36)	(2.71)	(2.03)	(5.87)	(4.88)	(6.30)	(4.80)	
price	-0.030	-0.033	-0.039*	-0.019	-0.023	-0.126***	-0.061***	-0.080***	-0.074***	-0.064*	0.002	-0.133***	-0.042***	-0.044**	-0.055
	(-1.54)	(-1.32)	(-1.67)	(-0.90)	(-0.83)	(-3.73)	(-3.08)	(-5.82)	(-2.67)	(-1.80)	(0.12)	(-4.66)	(-2.60)	(-2.55)	
illiquid	0.075***	0.017	-0.008	0.019	-0.009	0.005	-0.006	-0.040	-0.038	-0.010	0.045**	-0.070***	0.042***	0.004	0.002
	(4.51)	(0.99)	(-0.28)	(1.02)	(-0.36)	(0.16)	(-0.25)	(-1.03)	(-1.55)	(-0.34)	(2.09)	(-2.82)	(2.81)	(0.35)	
cgs	0.126***	0.078**	0.084**	0.103***	0.094*	0.156***	0.063*	-0.030	0.106***	0.094**	0.039	0.148***	0.105***	0.025	0.085
	(3.88)	(2.04)	(2.54)	(3.79)	(1.86)	(2.96)	(1.87)	(-0.89)	(3.10)	(2.17)	(1.62)	(3.78)	(3.16)	(0.76)	
ID	0.096***	0.054**	-0.012	0.038*	0.027	0.013	-0.033	-0.023*	0.001	0.005	0.029*	0.036	0.040**	0.002	0.020
	(4.20)	(2.48)	(-0.58)	(1.77)	(0.90)	(0.42)	(-1.33)	(-1.76)	(0.05)	(0.12)	(1.67)	(1.36)	(2.08)	(0.10)	
failure	-0.072***	-0.044*	-0.055**	-0.030	0.006	-0.104***	-0.056**	-0.072***	-0.084***	0.001	0.009	-0.055*	-0.175***	-0.013	-0.053
	(-3.79)	(-1.88)	(-2.23)	(-1.23)	(0.16)	(-3.20)	(-2.42)	(-6.40)	(-3.13)	(0.03)	(0.44)	(-1.96)	(-6.89)	(-0.68)	
max-ret	0.212***	0.272***	0.087***	0.140***	0.095**	0.080**	0.031	0.050**	0.123***	0.071*	0.027	0.061*	-0.056*	0.109***	0.093
	(7.41)	(8.71)	(3.15)	(4.63)	(2.18)	(2.14)	(1.18)	(2.13)	(2.83)	(1.95)	(1.07)	(1.69)	(-1.84)	(3.16)	
dur	-0.015	0.002	0.011	-0.001	-0.023	0.062*	-0.004	-0.001	-0.049**	0.021	0.057***	-0.014	0.011	0.044***	0.007
	(-0.80)	(0.11)	(0.56)	(-0.04)	(-0.93)	(1.92)	(-0.19)	(-0.11)	(-2.24)	(0.76)	(3.40)	(-0.72)	(0.76)	(2.96)	
ag	0.015	0.00987	0.035*	0.022	-0.022	0.009	-0.001	0.038***	-0.014	-0.014	0.046***	0.038	0.019	-0.0003	0.013
	(0.79)	(0.57)	(1.73)	(1.17)	(-0.82)	(0.30)	(-0.03)	(4.15)	(-0.62)	(-0.52)	(2.80)	(1.55)	(1.42)	(-0.03)	
P52-WH	0.290***	0.282***	0.036	0.130***	0.265***	0.258***	0.096***	-0.011	0.158***	0.131**	0.060*	0.162***	0.213***	0.055	0.152
	(10.06)	(8.89)	(0.92)	(3.70)	(5.14)	(5.10)	(2.67)	(-0.30)	(2.92)	(2.42)	(1.89)	(3.80)	(8.29)	(1.40)	
cogs	0.029	0.018	0.024	0.001	0.082***	0.104***	-0.027	-0.011	0.052**	0.081***	0.006	0.032	0.003	-0.009	0.027
	(1.52)	(0.82)	(1.64)	(0.04)	(3.25)	(4.10)	(-1.30)	(-1.44)	(2.41)	(2.63)	(0.35)	(1.39)	(0.24)	(-0.63)	
rev-vola	-0.022	-0.012	-0.024	0.001	-0.001	0.009	-0.016	0.003	-0.054*	0.010	0.038*	-0.019	0.020	0.039**	-0.002
	(-0.95)	(-0.48)	(-1.19)	(0.05)	(-0.04)	(0.18)	(-0.71)	(0.32)	(-1.87)	(0.28)	(1.85)	(-0.79)	(1.29)	(2.58)	
avg.	0.064	0.060	0.028	0.039	0.053	0.060	0.019	-0.001	0.019	0.036	0.041	0.031	0.034	0.028	0.036
avg. without IVOL and mom-str	0.056	0.054	0.023	0.034	0.047	0.052	0.013	-0.003	0.011	0.030	0.037	0.026	0.029	0.025	0.031
# abs. value t-stat > 2	11	9	8	7	8	11	6	6	8	6	9	7	10	9	8.21

Table 7: Fama-MacBeth Regressions Multivariate

This table shows multivariate Fama-MacBeth regression results of momentum profits on size-decile, rsquared-decile, turnover-decile, age-decile, analyst- coverage-decile, forecast-dispersion-decile, book-to-market-decile, price- decile, illiquidity-decile, capital-gains-decile, information-diffusion-decile, failure-probabiltiy-decile, maximum-daily return-decile, equity-duration- decile, asset-growth-decile, 52-week-high-price-decile, cost-of-goods- decile, and revenue-volatility-decile, momentum strength decile, and IVOL rank simultaneously (i.e. multivariate regressions) for each country separately. Within each country, all missing values of characteristics are replaced by (monthly) means. Characteristic deciles are calculated by the end of each month. With regard to size, r-squared, age, analyst coverage, book-to-market, price, information diffusion, and maximum daily return, deciles are ranked in descending order. For illustration purposes, all regression coefficients are multiplied by 100. Respective t-statistics are indicated within parentheses. Significance levels are shown as follows: * displays significance at the 10% level, ** significance at the 5% level and *** significance at the 1% level. The sample runs from M1:1989 to M12:2015. Monthly returns are winsorized at the 0.02% and 99.8% levels. Stocks in the lowest market capitalization decile are excluded from the analysis. Months exhibiting below 100 stocks are excluded from the analysis as well.

	atl	can	fra	ger	hkg	ind	ita	jap	mal	sok	swi	tai	uni	usa	avg.
size	-0.103*	0.110	0.025	-0.051	0.183	-0.120	-0.086	-0.084***	0.115*	0.659**	-0.033	0.203	-0.072	-0.018	0.052
	(-1.77)	(1.29)	(0.58)	(-1.08)	(0.50)	(-1.42)	(-1.01)	(-3.11)	(1.83)	(2.01)	(-0.74)	(1.53)	(-1.49)	(-0.62)	
R^2	0.049	0.013	-0.004	0.045	0.343	-0.035	0.020	0.001	0.086*	-0.075	0.045	-0.267**	0.019	0.021	0.019
	(1.64)	(0.22)	(-0.15)	(1.47)	(1.13)	(-0.77)	(0.41)	(0.09)	(1.74)	(-0.94)	(1.43)	(-2.58)	(0.83)	(1.45)	
turn	0.016	0.059	0.034	0.086*	0.409	0.026	-0.038	0.052***	-0.058	-0.172	0.042	-0.058	0.023	0.022	0.032
	(0.48)	(1.28)	(1.10)	(1.73)	(1.03)	(0.41)	(-0.60)	(3.03)	(-0.97)	(-1.38)	(1.32)	(-0.53)	(1.00)	(1.31)	
age	0.028	-0.026	0.029	0.015	0.027	0.025	-0.024	-0.010	0.048	0.019	0.029	0.031	-0.006	0.040***	0.016
	(1.06)	(-0.80)	(1.40)	(0.58)	(0.12)	(0.39)	(-0.52)	(-0.53)	(1.37)	(0.24)	(0.93)	(0.31)	(-0.34)	(3.41)	
nanalyst	0.025	0.024	0.041	0.108	0.685	0.178**	0.027	0.050	0.110	-0.111	0.118**	0.030	0.047	0.045**	0.098
	(0.54)	(0.49)	(0.99)	(1.63)	(1.13)	(2.41)	(0.38)	(1.56)	(1.46)	(-0.40)	(2.29)	(0.20)	(1.52)	(2.26)	
eps-disp	0.040	0.063	0.014	-0.018	-0.062	0.005	0.016	0.021*	-0.011	0.028	-0.056**	0.222***	0.025	0.017	0.022
	(1.50)	(0.77)	(0.65)	(-0.71)	(-0.60)	(0.12)	(0.34)	(1.91)	(-0.25)	(0.38)	(-2.09)	(2.92)	(1.23)	(1.57)	
bm	0.060*	0.185***	0.068**	0.132***	-0.224	-0.045	0.122**	0.088***	-0.104*	0.099	0.051	0.151	0.065***	0.091***	0.053
	(1.92)	(3.09)	(2.49)	(3.70)	(-1.51)	(-0.59)	(2.27)	(5.50)	(-1.85)	(1.02)	(1.37)	(0.93)	(3.43)	(6.13)	
price	-0.011	0.016	-0.064**	0.020	-0.115	-0.015	-0.089**	-0.005	-0.135*	-0.066	0.003	-0.250	0.062***	-0.068***	-0.051
	(-0.28)	(0.22)	(-2.32)	(0.49)	(-0.53)	(-0.24)	(-1.99)	(-0.30)	(-1.84)	(-0.55)	(0.10)	(-1.39)	(2.84)	(-3.38)	
illiquid	0.134**	-0.002	0.010	0.042	-0.048	0.074	0.119	0.091***	-0.203**	-0.437*	0.054	-0.104	0.128***	0.050	-0.007
	(2.27)	(-0.03)	(0.21)	(0.65)	(-0.13)	(0.93)	(1.11)	(3.57)	(-2.57)	(-1.70)	(1.05)	(-0.71)	(2.73)	(1.57)	
cgs	-0.014	-0.052	0.0004	0.066*	0.103	0.020	-0.052	-0.005	0.054	-0.037	0.002	0.050	0.021	-0.021	0.010
	(-0.32)	(-0.92)	(0.01)	(1.68)	(0.59)	(0.34)	(-1.08)	(-0.17)	(1.03)	(-0.50)	(0.08)	(0.61)	(0.44)	(-0.79)	
ID	0.051**	0.077	-0.014	0.018	-0.084	-0.001	0.075*	-0.040**	-0.051	0.033	0.016	0.195**	-0.007	0.005	0.019
	(2.02)	(1.33)	(-0.64)	(0.62)	(-0.83)	(-0.02)	(1.94)	(-3.10)	(-0.99)	(0.42)	(0.58)	(2.31)	(-0.44)	(0.38)	
failure	-0.022	-0.115	-0.014	-0.012	0.077	-0.127**	-0.024	-0.035**	-0.084*	-0.128	0.037	-0.145	-0.170***	-0.040***	-0.057
	(-0.70)	(-1.33)	(-0.51)	(-0.27)	(0.81)	(-2.16)	(-0.58)	(-1.97)	(-1.67)	(-0.92)	(1.16)	(-1.50)	(-5.27)	(-2.62)	
max-ret	0.150***	0.243***	0.094***	0.0954***	0.175*	0.099*	-0.009	0.083***	0.073	0.095	0.007	0.040	0.001	0.106***	0.089
	(4.74)	(6.34)	(3.99)	(2.78)	(1.90)	(1.75)	(-0.23)	(3.92)	(1.33)	(1.17)	(0.22)	(0.68)	(0.02)	(4.10)	
dur	-0.021	-0.011	0.029	0.003	0.161	0.019	0.022	0.010	0.017	-0.026	0.016	-0.045	0.018	0.023*	0.0153
	(-0.78)	(-0.24)	(1.31)	(0.08)	(1.02)	(0.36)	(0.48)	(0.85)	(0.39)	(-0.29)	(0.48)	(-0.40)	(0.69)	(1.89)	
P52-WH	0.127***	0.080	-0.032	-0.042	0.036	0.268***	0.097*	-0.022	0.039	0.057	-0.028	-0.047	0.049	-0.025	-0.015
	(3.17)	(1.03)	(-0.81)	(-0.93)	(0.14)	(3.42)	(1.78)	(-0.56)	(0.44)	(0.49)	(-0.62)	(-0.49)	(1.36)	(-0.70)	
ag	0.014	-0.074	-0.023	-0.038	0.009	0.072	-0.046	0.005	-0.020	-0.036	-0.035	-0.043	0.021	-0.022*	0.040
	(0.55)	(-1.60)	(-1.04)	(-1.03)	(0.11)	(1.59)	(-1.14)	(0.46)	(-0.46)	(-0.46)	(-1.31)	(-0.65)	(0.81)	(-1.81)	
cogs	-0.006	0.016	0.024	-0.017	-0.127	0.102*	-0.020	-0.009	0.076	0.118*	-0.052**	-0.077	0.014	-0.003	0.003
	(-0.22)	(0.43)	(1.36)	(-0.63)	(-0.47)	(1.91)	(-0.57)	(-0.88)	(1.46)	(1.69)	(-2.07)	(-1.20)	(0.56)	(-0.21)	
rev-vola	-0.034	-0.019	-0.015	0.014	-0.084	0.032	0.0148	-0.007	0.066	-0.011	0.020	0.053	0.042	0.029***	0.007
	(-1.42)	(-0.46)	(-0.71)	(0.43)	(-0.57)	(0.69)	(0.38)	(-0.52)	(1.63)	(-0.13)	(0.71)	(0.66)	(1.39)	(2.74)	
mom-str	0.067**	0.134*	0.081***	0.085*	-0.090	0.024	0.041	0.022	0.062	0.171**	0.052*	0.010	0.050**	0.062***	0.055
	(2.02)	(1.69)	(3.00)	(1.86)	(-0.88)	(0.52)	(0.98)	(1.29)	(1.24)	(2.12)	(1.81)	(0.13)	(2.20)	(2.85)	
IVOL	0.009	0.009	0.015	0.013	-0.028	0.042*	0.039**	0.007	0.014	0.020	-0.007	0.059	0.027***	-0.001	0.016
	(0.55)	(0.30)	(1.44)	(0.80)	(-0.31)	(1.88)	(2.00)	(1.31)	(0.60)	(0.49)	(-0.46)	(1.35)	(2.92)	(-0.11)	
avg.	0.028	0.036	0.015	0.028	0.067	0.032	0.010	0.011	0.005	0.010	0.014	0.0003	0.018	0.016	0.021
avg. without IVOL and mom-str	0.027	0.033	0.011	0.026	0.081	0.032	0.007	0.010	0.001	0.001	0.013	-0.003	0.016	0.014	0.019

Table 8: Fama-MacBeth Regressions on Predicted Momentum Profits

This table reports Fama-MacBeth regressions of actual momentum profits on predicted momentum profit deciles only (univariate) as well as on predicted momentum profit deciles, actual momentum strength deciles, and actual IVOL ranks (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 deciles. For our internationally pooled sample, characteristics deciles are calculated transnationally on a monthly basis. Each month for each country, we then run ordinary regressions of momentum profits on all eighteen characteristics deciles simultaneously (multivariate). Then, on a five-year rolling basis, we apply average regression coefficients and constants for each of our eighteen characteristics deciles 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 deciles (univariate) as well as on predicted momentum profits deciles, actual momentum strength deciles, and actual IVOL rank (multivariate). For illustration purposes, all coefficients are multiplied by 100. Respective t-statistics are indicated within parentheses. The sample runs from M1:1989 to M12:2015. Monthly returns are winsorized at the 0.01% and 99.9% levels. Stocks in the lowest market capitalization decile are excluded from the analysis. Months exhibiting below 100 stocks are excluded from the analysis as well.

	Predicted Mom	Predicted Mom	Mom-Str	IVOL
atl	0.3109	0.2784	0.1141	-0.0122
	(10.75)	(9.55)	(4.01)	(-1.32)
can	0.3328	0.3210	0.0689	-0.0109
	(11.15)	(9.18)	(2.10)	(-1.11)
fra	0.0898	0.0869	0.1027	-0.0019
	(2.90)	(3.77)	(3.12)	(-0.25)
ger	0.1525	0.1281	0.1010	0.0057
	(5.12)	(4.80)	(3.42)	(0.76)
hkg	0.2276	0.2201	0.0491	0.0002
	(5.60)	(5.47)	(1.32)	(0.01)
ind	0.2619	0.2459	0.0423	0.0496
	(5.03)	(5.14)	(1.06)	(3.61)
ita	0.1269	0.1096	0.0825	0.0142
	(4.85)	(4.58)	(2.67)	(1.41)
jap	0.0983	0.1066	0.0243	0.0020
	(4.57)	(5.20)	(1.03)	(0.44)
mal	0.1810	0.1726	0.0730	-0.0072
	(5.00)	(4.98)	(1.94)	(-0.62)
sok	0.1550	0.1312	0.0803	0.0111
	(3.58)	(3.29)	(1.75)	(0.82)
swi	0.0962	0.0734	0.0598	0.0143
	(3.90)	(3.45)	(2.44)	(1.72)
tai	0.1433	0.1297	0.0580	-0.0129
	(5.00)	(4.23)	(1.65)	(-1.18)
uni	0.2425	0.2340	0.0705	-0.0030
	(9.14)	(9.26)	(2.68)	(-0.43)
usa	0.1438	0.1464	0.0430	-0.0005
	(6.59)	(8.41)	(1.43)	(-0.08)
internat	0.2158	0.2106	0.0467	0.0000
	(12.14)	(13.26)	(2.42)	(0.01)

Table 9: Double-Sorts on Predicted Momentum Profits

This table reports average monthly returns obtained from ordinary double-sorts on predicted momentum profits (first-sort) and on past returns (second-sort), 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. At the end of each month, for each country we sort predicted momentum profits into quintiles. Within each quintile, we calculate ordinary momentum strategies. This means we go long the quintile of past return (t-6,t-1) winners and short the quintile of past return (t-6,t-1) losers (P5-P1). We then calculate the differences between momentum returns of the highest and the lowest quintile. 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. For our internationally pooled sample, characteristics deciles are calculated transnationally on a monthly basis. Each month, for each country we then run ordinary regressions of momentum profits on all eighteen characteristics deciles simultaneously (multivariate). Then, on a five-year rolling basis, we apply average regression coefficients and constants for each of our eighteen characteristics deciles. We predict momentum profits for the next month solely upon the basis of our chosen set of characteristics. Respective t-statistics are indicated within parentheses. The sample runs from M1:1989 to M12:2015. Monthly returns are winsorized at the 0.01% and 99.9% levels. Stocks in the lowest market capitalization decile are excluded from the analysis. Months exhibiting below 100 stocks are excluded from the analysis as well.

		Q1	Q2	Q3	Q4	Q5	Ret Diff
atl	P5-P1	0.59%	0.81%	1.54%	1.66%	2.60%	2.01%
		(1.56)	(1.95)	(3.27)	(3.46)	(4.61)	(3.01)
	P5	0.42%	1.01%	1.35%	2.21%	2.26%	
	P1	-0.18%	0.21%	-0.19%	0.56%	-0.34%	
can	P5-P1	0.08%	0.15%	1.46%	1.07%	2.32%	2.25%
		(0.19)	(0.32)	(2.78)	(2.24)	(4.28)	(3.52)
	P5	0.66%	0.61%	1.51%	1.36%	1.83%	
	P1	0.59%	0.46%	0.05%	0.30%	-0.50%	
fra	P5-P1	0.23%	0.91%	0.94%	1.01%	1.19%	0.96%
		(0.62)	(2.61)	(2.10)	(2.22)	(1.91)	(1.47)
	P5	1.23%	1.30%	1.34%	1.81%	1.58%	
	P1	1.00%	0.39%	0.39%	0.80%	0.40%	
ger	P5-P1	0.21%	0.99%	0.88%	1.94%	2.59%	2.38%
		(0.65)	(2.85)	(2.16)	(3.81)	(4.34)	(3.73)
	P5	0.79%	1.30%	0.88%	1.78%	1.99%	
	P1	0.58%	0.32%	0.00%	-0.16%	-0.60%	
hkg	P5-P1	0.02%	0.19%	0.69%	1.59%	1.63%	1.62%
		(0.03)	(0.32)	(1.10)	(2.55)	(2.31)	(1.86)
	P5	0.17%	0.61%	0.78%	1.46%	1.36%	
	P1	0.15%	0.42%	0.09%	-0.12%	-0.27%	
ind	P5-P1	0.39%	0.19%	0.45%	1.55%	1.31%	0.92%
		(0.78)	(0.32)	(0.71)	(2.52)	(1.77)	(1.06)
	P5	1.23%	1.47%	1.79%	2.83%	2.74%	
	P1	0.84%	1.28%	1.34%	1.28%	1.43%	
ita	P5-P1	0.39%	0.51%	0.55%	1.00%	1.75%	1.37%
		(0.96)	(1.11)	(1.16)	(1.66)	(3.26)	(2.19)
	P5	0.80%	1.07%	1.12%	1.47%	1.50%	
	P1	0.41%	0.56%	0.57%	0.47%	-0.25%	
jap	P5-P1	-0.58%	-0.10%	-0.01%	0.27%	0.98%	1.56%
		(-1.75)	(-0.33)	(-0.02)	(0.77)	(2.21)	(3.34)
	P5	0.10%	0.34%	0.36%	0.34%	0.51%	
	P1	0.68%	0.44%	0.37%	0.07%	-0.47%	
mal	P5-P1	0.57%	-0.41%	-0.51%	0.72%	0.96%	0.39%
		(1.00)	(-0.46)	(-1.08)	(1.16)	(1.74)	(0.56)
	P5	0.67%	0.19%	0.17%	1.11%	1.31%	
	P1	0.10%	0.60%	0.68%	0.38%	0.35%	
sok	P5-P1	-0.29%	0.44%	0.05%	0.93%	1.65%	1.93%
		(-0.46)	(0.86)	(0.08)	(1.18)	(1.83)	(1.83)
	P5	0.94%	1.02%	1.06%	1.64%	1.27%	
	P1	1.23%	0.58%	1.01%	0.71%	-0.38%	
swi	P5-P1	1.03%	0.91%	0.69%	1.54%	2.11%	1.08%
		(3.05)	(2.70)	(2.02)	(3.41)	(3.62)	(1.87)
	P5	1.48%	1.36%	1.26%	1.73%	2.12%	
	P1	0.46%	0.45%	0.57%	0.19%	0.01%	
tai	P5-P1	-0.30%	0.34%	0.35%	0.33%	1.23%	1.52%
		(-0.60)	(0.64)	(0.59)	(0.54)	(1.93)	(2.23)
	P5	0.50%	0.91%	1.07%	0.26%	0.92%	
	P1	0.80%	0.57%	0.72%	-0.07%	-0.31%	
uni	P5-P1	0.11%	0.85%	1.10%	1.64%	1.67%	1.56%
		(0.33)	(2.56)	(2.83)	(3.68)	(4.07)	(3.18)
	P5	0.58%	1.01%	1.18%	1.44%	1.98%	
	P1	0.47%	0.16%	0.08%	-0.21%	0.31%	
usa	P5-P1	-0.11%	0.24%	0.29%	0.91%	1.51%	1.63%
		(-0.33)	(0.66)	(0.75)	(2.19)	(3.21)	(4.04)
	P5	1.02%	1.20%	1.14%	1.51%	1.59%	
	P1	1.13%	0.96%	0.85%	0.60%	0.08%	
internat	P5-P1	-0.29%	-0.04%	0.55%	1.27%	2.19%	2.48%
		(-0.88)	(-0.10)	(1.60)	(3.58)	(5.37)	(6.23)
	P5	0.33%	0.53%	0.79%	1.16%	1.53%	
	P1	0.62%	0.57%	0.24%	-0.10%	-0.65%	

Table 10: 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 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 deciles. For our internationally pooled sample, characteristics deciles are calculated transnationally on a monthly basis. Each month, for each country we then run ordinary regressions of momentum profits on all eighteen characteristics deciles simultaneously (multivariate). Then, on a five-year rolling basis, we apply average regression coefficients and constants for each of our eighteen characteristics deciles 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 and the beta coefficient on the momentum factor (WML). Respective t-statistics are indicated within parentheses. The sample runs from M1:1989 to M12:2015. Monthly returns are winsorized at the 0.01% and 99.9% levels. Stocks in the lowest market capitalization decile are excluded from the analysis. Months exhibiting below 100 stocks are excluded from the analysis as well.

	Ret Diff	Skew	Kurt	Min	Constant	WML Beta
atl	2.10%	-0.07	4.94	-49.28%	0.0132	0.2565
	(3.01)				(1.80)	(2.04)
can	2.50%	-0.20	3.81	-39.04%	0.0186	0.1993
	(3.52)				(2.80)	(2.15)
fra	0.96%	-0.73	7.89	-52.66%	0.0105	-0.1069
	(1.47)				(1.55)	(-0.85)
ger	2.38%	-0.57	5.60	-44.36%	0.0222	-0.0080
	(3.73)				(3.35)	(-0.07)
hkg	1.62%	-0.27	4.03	-42.03%	0.0086	0.1950
	(1.86)				(0.97)	(1.51)
ind	0.92%	-0.23	4.25	-43.86%	0.0038	0.0346
	(1.06)				(0.43)	(0.26)
ita	1.37%	0.06	4.98	-39.91%	0.0118	0.2155
	(2.19)				(1.86)	(1.76)
jap	1.56%	0.03	6.18	-33.08%	0.0137	0.1999
	(3.34)				(2.91)	(1.92)
mal	0.39%	0.48	5.73	-27.34%	0.0053	0.0530
	(0.56)				(0.74)	(0.53)
sok	1.93%	-1.23	19.34	-127.86%	0.0169	0.0379
	(1.83)				(1.58)	(0.26)
swi	1.08%	-0.67	6.62	-46.46%	0.0110	0.0663
	(1.87)				(1.82)	(0.59)
tai	1.52%	-0.34	4.21	-31.83%	0.0167	0.0442
	(2.23)				(2.41)	(0.31)
uni	1.56%	0.08	5.00	-32.56%	0.0184	-0.0493
	(3.18)				(3.57)	(-0.52)
usa	1.63%	0.20	5.60	-23.38%	0.0184	-0.1678
	(4.04)				(4.46)	(-2.35)
internat	2.48%	-0.09	5.03	-23.63%	0.0201	0.3297
	(6.23)				(4.63)	(2.85)