DISCUSSION PAPER SERIES

No. 10804

SIZE AND MOMENTUM PROFITABILITY IN INTERNATIONAL STOCK MARKETS

Peter S. Schmidt, Andreas Schrimpf, Urs von Arx,
Alexander F. Wagner and Andreas Ziegler

FINANCIAL ECONOMICS

Centre for Economic Policy Research

ISSN 0265-8003

SIZE AND MOMENTUM PROFITABILITY IN INTERNATIONAL STOCK MARKETS

Peter S. Schmidt, Andreas Schrimpf, Urs von Arx, Alexander F. Wagner and Andreas Ziegler

Discussion Paper No. 10804
September 2015
Submitted 28 August 2015

Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801
www.cepr.org

SIZE AND MOMENTUM PROFITABILITY IN INTERNATIONAL STOCK MARKETS[†]

Abstract

We study the link between the profitability of momentum strategies and firm size, drawing on an extensive dataset covering 23 stock markets across the globe. We first present evidence of an “extreme” size premium in a large number of countries. These size premia, however, are most likely not realizable due to low stock market depth. We also show that international momentum profitability declines sharply with market capitalization. Momentum premiums are also considerably diminished by trading costs, when taking into account the actual portfolio turnover incurred when implementing this strategy. In contrast to strategies based on size, we find that momentum premia especially for medium-sized stocks still remain economically and statistically significant in most equity markets worldwide after adjusting for transaction costs.

JEL Classification: C89, G12 and G15
Keywords: asset pricing anomalies, international equity markets, momentum, size and transaction costs

Peter S. Schmidt peter.steffen.schmidt@googlemail.com
University of Zurich

Andreas Schrimpf andreas.schrimpf@bis.org
Bank for International Settlements

Urs von Arx uva-zh-49@bluewin.ch
ETH Zurich

Alexander F. Wagner alexander.wagner@bf.uzh.ch
University of Zurich and CEPR

Andreas Ziegler andreas.ziegler@uni-kassel.de
University of Kassel

[†] The authors appreciate financial support from the Swiss National Science Foundation, the Commission for Technology and Innovation of the Swiss Confederation (CTI), the Swiss Finance Institute, and the NCCR FINRISK (project B1: Corporate Finance, Market Structure and the Theory of the Firm) as well as financial and infrastructural support from the Zurich Cantonal Bank (ZKB). We are grateful to Harald Lohre for useful comments and suggestions at the beginning of our project. Helpful research assistance of Katja Bächtold, Pascal Bücheler, Carolin Hecht, Marco Rudin and Veronika Sharonova is gratefully acknowledged. A special thanks goes to Tatjana-Xenia Puhan who helped us to expand the dataset to additional countries. Furthermore we thank all researchers who contacted us regarding the dataset. Their comments helped to improve the dataset as well as the paper at hand. A former version of this paper circulated under the title ‘On the Construction of Common Size, Value and Momentum Factors in International Stock Markets: A Guide with Applications’.

1. Introduction

This paper investigates the interplay between size and momentum strategies in international stock markets. A main focus of our work is to determine if any size and momentum profits are indeed realizable in the practical implementation of investment strategies or whether they have to be deemed illusory. Our analysis is motivated by the fact that researchers and practitioners alike are increasingly eager to determine the existence or non-existence of equity market anomalies across the globe. Besides allowing for an analysis of the common roots of a specific anomaly, relying on international data can help address a common objection that anomalies observed in the US market alone may possibly be a manifestation of survivorship or data-snooping biases (Kothari et al., 1995; Lo and MacKinlay, 1990; MacKinlay, 1995).

Since the discovery of the so-called size effect by Banz (1981) this issue has been controversially discussed.[1] On the one hand, some authors claim that the size premium is diminishing since its discovery and has completely vanished thereafter (e.g. Dimson and Marsh, 1999, for the UK; Horowitz et al, 2000; Schwert, 2003, for the US). On the other hand, in practice a size premium continues to be employed frequently in cost of capital calculations. It is, therefore, of significant interest to investigate whether a size premium exists in individual countries.

As for momentum, Jegadeesh and Titman (1993) show for the US that stocks having performed well in the past twelve months perform significantly better in the next 3-12 months than stocks which have performed poorly in the past twelve months. In applications, researchers frequently include a momentum factor when modeling expected returns. While the existence of momentum profits internationally has been shown before (e.g. Chui et al. 2010, Rouwenhorst 1998), the evidence on the interrelation of size and momentum in international markets is less clear. Some studies (e.g. Hong et al., 2000) find that the biggest stocks provide smaller momentum returns than smaller ones, supporting the hypotheses of Hong and Stein (1999). Other studies, however, find no support (e.g. Israel and Moskowitz, 2013).

For both size and the momentum strategies, it is critical from a practical perspective to also develop a sense of the feasibility of these strategies once trading costs and market depth are taken into account. To

[1] For a recent overview of the topic see, for example, van Dijk (2011).

conduct these analyses, we require a dataset of common risk factors in international stock markets. Specifically, in the first part of the paper, we show how two widely accessible databases, Thomson Reuters Datastream (TRD) and Thomson Reuters Worldscope (TRW), can be used to construct an internally consistent, replicable financial dataset for the US and a broad range of other countries across the globe (all European OECD countries as well as Australia, Canada, Hong Kong, Japan, and Singapore) from which the well-known risk factors according to Carhart (1997), including the market, value (HML – high-minus-low), size (SMB – small-minus-big), and momentum (WML – winners-minus-losers) risk factors can be derived. We put considerable emphasis on explaining the detailed procedure so as to allow other researchers to follow these steps or to depart from them where they find it appropriate. While several authors are offering datasets partially overlapping with our dataset, we believe that a fully explicit description of the choices made in the construction, as well as a set of consistency checks hopefully ensure a particularly high level of reliability of the data we provide.[2]

To ensure that our dataset meets high quality standards, we conduct several consistency checks. First, we compare the market returns and risk factors for the US, Europe, and Japan based on TRD and TRW data with important benchmarks, namely, the market returns and momentum, size, and value risk factors obtained from CRSP/COMPUSTAT data, as available on the website of Kenneth French, from here on referred to as the FF data (according to Fama and French, 1993). We find that our market returns and risk factors are very similar to the FF counterparts. Second, the reliability of our dataset is strengthened by additional comparisons for stock portfolios which are separately sorted on size, book-to-market equity (BE/ME), and momentum as well as jointly sorted on size-BE/ME and size-momentum. Third, we compare single international market returns with corresponding well-known representative

[2] Some studies use proprietary, country-specific datasets which are in general inaccessible to other researchers while other studies compile datasets from various sources. Griffin (2002), for example, uses data from the Pacific-Basin Capital Markets database (Japan), Thomson Reuters Datastream (U.K. and Canada) and CRSP/COMPUSTAT (US). Schrimpf et al. (2007) and Ziegler et al. (2007) use a database maintained at Humboldt University, Berlin, Germany. Further country-specific studies include Ammann and Steiner (2008) (Switzerland), Artmann et al. (2012) (Germany), Dimson et al. (2003), Gregory et al. (2009), Nagel (2001) (all three U.K.). Additional examples of studies that have employed non-US data to study empirical asset pricing models include, besides the studies already mentioned, An and Ng (2010), Ang et al. (2008), Asness and Frazzini (2013), Bauer et al. (2010), Eun et al. (2010), Fama and French (1998, 2012), Ferreira et al. (2013), Heston et al. (1999), Hou et al. (2011), Leippold and Lohre (2012a, 2012b), Liew and Vassalou (2000), and Rouwenhorst (1998). In several cases, the constructed factors are not available to other researchers, though there are also important exceptions. Fama and French (2012), Asness and Frazzini (2013) and Hau and Lai (2014) freely provide their international risk factor data as well. We compare our data with Fama and French (2012) where it overlaps.

market indexes – an exercise rarely, if at all, conducted in other studies constructing international risk factor data. Our results show that these series are strongly correlated and similar in magnitude, suggesting that our data cover the respective markets well. Our dataset is freely available to other researchers, which hopefully facilitates research in empirical finance also in non-US markets.[3]

Our main results on the profitability of size and momentum are as follows. First, we do not find a significant size effect for any of the countries covered, when judged by the average return on the SMB factors. However, Banz (1981) already suggested that "*the size effect is not linear in the market value; the main effect occurs for very small firms while there is little difference in return between average sized and large firms*" (p. 3). Consequently, we consider an "extreme" size effect, namely, the difference in stock returns between the biggest 10% (in terms of market capitalization) and the smallest 10%. We find that the size effect (not adjusted for trading costs), when defined this way, appears to be alive and well in most of the countries we consider. Indeed, it also exists in many countries when considering the smallest and largest quintiles. In a related study, De Moor and Sercu (2013) find in a pooled international dataset that the smallest 10% of the firms earn a significant premium over the biggest 10 % firms. Our study first differs from theirs in that we examine various countries separately, allowing additional insights. Moreover, we use value weighted, instead of equal-weighted returns. Most importantly, as discussed below, we also evaluate the trading costs and the actual implementability of size-based trading strategies.

Next, we investigate the interplay between size and momentum. Hong et al. (2000) find for US data from 1980 to 1996 that *"... once one moves past the very smallest capitalization stocks (...) the profitability of momentum strategies declines sharply with market capitalization*" (p. 267). Our results for the international dataset from 1991 to 2012, constituting an out-of-sample test, confirm this finding for many individual countries. Our results are also in line with the results of Chui et al. (2010) who show that momentum profits across the world are negatively related to the median firm size in the respective markets. In contrast, we do not find support for the claim of Avramov et al. (2013) that momentum

[3] Since the circulation of the first version of our data in 2011, our factors have been employed by several researchers, and we thank them for providing us with valuable feedback. Brückner et al. (2014) compare our factors for Germany with datasets from other sources. Although our factor data naturally cannot address some aspects that only specialized, partly hand-collected data from dedicated country-specific research can address, our data seem to perform quite well relative to other datasets with an international scope.

strategies derive their profitability from shorting loser stocks. Moreover, we find a significant size premium for a portfolio containing the 30% of stocks with the highest degree of momentum (i.e. the highest past 2-12 month average returns).

Importantly, we examine whether these size and momentum strategies are still worthwhile when trading costs are included in the analysis. This is rarely done in academic studies but has received attention in the current literature (e.g. Frazzini et al., 2012; Novy-Marx and Velikov, 2014). We employ three approaches. First, we directly approximate trading costs by values based on Frazzini et al. (2012). Second, we compute critical (maximum) trading costs that an investor could occur and still earn significant excess returns. Third, we calculate the US dollar trading volume of the involved portfolios to assess whether the market has enough depth and capacity for such a quantitative strategy to be implementable in practice.

We find that size premiums, even where they exist, are most likely not realizable because the US dollar trading volumes of the involved portfolios are rather small. Momentum premiums are also diminished by trading costs to a considerable extent. That said, for most countries momentum premia still remain statistically and economically significant, especially for medium-sized stocks.

The paper proceeds as follows. Section 2 deals with the data preparation, explains the general construction of the risk factors and compares our novel market returns and risk factors with those on the basis of other data sources. Section 3 presents the empirical baseline results for size and momentum strategies. Section 4 includes trading cost measures. Section 5 concludes.

2. Data

Section 2.1 describes briefly the data preparation process and the construction of the risk factors proposed by Fama and French (1993) and Carhart (1997). A detailed treatment is given in Appendix A.1 (Data preparation) and Appendix A.2 (Common risk factors). Section 2.2 compares US market returns and common risk factors from our dataset with the corresponding series from Kenneth French’s website..

Section 2.3 conducts checks for the non-US markets. We compare self-created local market indices with publicly available local market indices. While this exercise is not usually conducted in studies using or providing international factor data, it is an essential benchmark for evaluating the usefulness of any common risk factors then calculated. Moreover, we compute pan-European as well as Japanese stock market returns and common risk factors from our dataset and compare them with another publicly available dataset.

2.1. Data preparation, common risk factors, risk-free rates

The data preparation process employs static and dynamic screens as suggested by Ince and Porter (2006) as well as additional filters. Although TRW data is in principle available from 1980 onwards, we often use a later starting date because the coverage is lower in the first years. Therefore, in a dataset starting in 1980 big firms would be most likely overrepresented. We hence use a time period from 1986 (with book equity values from 1985) to 2012 for the US and a time period from 1991 to 2012 for most of the other countries (coverage for some countries is too limited before 1989).[4] We screen the data for static (information does not change over time) as well as dynamic (information changes over time) criteria. The static screens are, for example, the geographic location, the type of instrument, the listing type, or the exchange mnemonic. Thus, we only include stocks which are domestic, of the equity type, a major listing, and from a domestic exchange. The dynamic screens remove constant prices at the end of our time period, truncate a certain proportion at the lower end of the (unadjusted) price distribution, or perform sanity checks whether some TRD calculations do make sense, amongst other checks. The removal of constant prices at the end of the time period is due to the fact that TRD reports for delisted stocks the last valid price (and also total return index) information. The removal of small (or penny) stocks is common in the literature. Sanity checks verify, for example, whether (unadjusted) price times number of shares yields the market value. For a complete discussion of both static and dynamic screens, see Appendix A.1.

[4] In Appendix A.3 we describe the updating procedure in detail.

The common risk factors proposed by Fama and French (1993) are widely used in the asset pricing literature to control for systematic risk. Occasionally, the momentum factor proposed by Carhart (1997) is added to the model put forth by Fama and French (1993). In this paper we closely reproduce the factors in the manner of Fama and French (1993). A detailed account is given in Appendix A.2 . Furthermore, we use the 3-month Treasury bill rate as the risk free rate proxy. For countries where no Treasury bill is available, we usually use a combination of the interbank rate and the overnight indexed swap (OIS) rate. For details see Appendix A.4 .

2.2. Results for the US stock market

To confirm the quality of the common risk factors and test portfolios compiled using TRD, we compare these data with the well-known data provided by Kenneth French. Table 1 shows averages (avg.), standard deviations (σ) and t-statistics (t) for value weighted US market returns from the FF and our TRD and TRW datasets as well as correlations between both return series (ρ) over time. The value weighted market returns are quite similar, with an average monthly return of 0.85% for the FF series and an average monthly return of 0.86% for our series. The correlation coefficient between the two value weighted returns is 0.94.

[Table 1 here]

We now analyze the time series of the US SMB, HML, and WML factors.[5] The corresponding results are also shown in Table 1. The average values for the SMB factors are rather low and amount to 0.10% (FF data) and 0.11% (our TRD and TRW data) per month. The correlation coefficient between the two SMB factors based on the FF and our TRD and TRW datasets is 0.93. The HML factors yield higher average values than the SMB factors and are very similar with 0.25% per month for the FF dataset and 0.28% per

[5] We explain the construction of theses factor in section A.2.1 in detail.

month for our dataset. The correlation coefficient between the two HML factors is 0.88. The WML factors have the highest average values with 0.53% per month (FF data) and 0.64% per month (our TRD and TRW data). The correlation coefficient between both factors is 0.93.

In sum, we are able to replicate very closely the properties of the benchmark risk factors, suggesting that the screens are effective in transforming the raw data into a data series suitable for further analysis.[6]

2.3. Results for the international stock markets

2.3.1. Market returns for single countries

To evaluate the quality of our dataset we compare self-created market indices from different countries with market indices available on TRD. In Table 2 we present results for the market returns of twenty-nine countries. We report monthly average percentage values of known local indices with a sufficiently long time series, as well as value weighted and equal weighted market returns calculated from our data. Furthermore, we present correlation coefficients of the value weighted and equal weighted market returns with the respective index(es). Two time periods are examined: a long period (07/1989 – 06/2012) and a short period (07/1999 – 06/2012).[7]

[Table 2 here]

There are differences by construction between the publicly available local indexes, which we use for comparison, and our value weighted indexes. First, the local indexes are usually calculated with the free float market capitalization as index weights, whereas we use total market capitalization. Second, we use price and dividend data to compile the indices, whereas some local indexes incorporate only price

[6] In addition in Appendix A.2.3, we investigate the quality of our dataset by comparing single and double sorted stock portfolio groups on various characteristics from Kenneth French's dataset with ours.

[7] Although a few markets seem to have a broad coverage back to 1986, most markets are covered much better a few years later. To report results as uniformly as possible for all markets considered, we choose 07/1989 as the start date when possible. Furthermore, for all countries except the US we have more recent data, allowing us to use a later end date (06/2012 instead of 02/2012). Further exemptions are indicated in Table 2.

information.[8] When possible, we use TRD total return indices, which include dividend payments. However, these indices are not always available and therefore we use also pure price indices for comparison purposes.[9] The third difference is that indexes like FTSE or MSCI do not include all stocks available because of the limited investability of small stocks. The remaining indices are either broad market indices (BAS (Belgium), TT (Canada), ISEQ (Ireland), TOPIX (Japan), SPI (Switzerland), LSE (Luxembourg), WGI (Poland), ICEXALL (Iceland)), indices restricted to a certain number of firms (CAC40 (France), AEX (Netherlands), RUSSELL (US)), or indices which cover a certain portion of the total market capitalization (HS (Hong Kong), BUX (Hungary), SAX (Slovakia)).

Panel A reports the results for all countries with available data for both periods. Panels B-H report results for countries for which we use different time periods, due to data availability restrictions.[10]

The main result of this analysis is that for the twenty-five biggest international stock markets[11] the correlations of our value weighted market returns with the local indices for the 07/1999 – 06/2012 period are at least 0.94. Furthermore, it is a satisfying result that for the biggest stock markets our indices are almost perfectly correlated with the benchmark indices. For the thirteen biggest stock markets (USA, Japan, UK, France, Canada, Germany, Hong Kong, Australia, Switzerland, Spain, Italy, the Netherlands and Sweden), they all have at least correlations of 0.95 (0.94) in the period 07/1999 – 06/2012 (07/1989 – 06/2012) with the respective benchmarks. Correlation coefficients in all countries are at least 0.87 (0.94) for the long (short) period except for Luxembourg, Slovakia (data are only available for the short period),

[8] For example, the US value weighted CRSP market return without dividends is on average 0.14 percentage points (per month) lower than the CRSP value weighted market return with dividends for the period ranging from July 1986 to December 2008.

[9] The Swiss Performance index (SPI), the Warsaw General Index (WGI), The Share Index of the Budapest Stock Exchange (BUX) and the Slovak Share Index (SAX) include dividend payments by construction. Furthermore, we use total return indices for the following countries: Australia (both periods), Austria (short period), Canada (both periods), Denmark (short period), Finland (short period), France (both periods), Germany (short period), Hong Kong (short period), Ireland (both periods), Italy (short period), Japan (both periods), Netherlands (both periods), Norway (short period), Portugal (both periods), Singapore (both periods), Spain (short period), Sweden (short period), Turkey (both periods), U.K. (both periods), US (both periods), Luxembourg (second period), Greece (both periods), Hungary (MSCI) and Czech Republic (both periods). All other indices are pure price indices.

[10] For the sake of clarity we do not report more than one comparison index. The only exception is Hungary for which we report in the second period also results for the MSCI index, besides the BUX, for which we report results for both periods. Since the BUX is a blue chip index and covers only the largest companies traded on the Budapest Stock Exchange (which contains thirteen firms in May 2010), the MSCI index is in principle better suited than the BUX. However, in the first period this index is not completely available (in contrast to the BUX).

[11] Table A.22 lists all countries in the dataset on their market capitalizations as by June 2011. All further remarks about aggregated market size of the countries refer to Table A.22.

and Iceland (data are only available for the 01/2001 – 06/2012 period).[12]

In sum, we conclude that our international dataset yields, with some exceptions for tiny markets, quite reliable results after the correction of data errors as described in this paper.

2.3.2. Market returns and common risk factors for Pan-Europe and Japan

Panel A of Table 3 shows averages (avg.), standard deviations (σ) and t-statistics (t) for value weighted pan-European market returns from the FF and our TRD and TRW datasets as well as correlations between both return series (ρ) over time. The value weighted market returns are similar for both datasets and on average 0.78% per month for the FF data and 0.77% for our data. The correlation of the two series is 0.94 and therefore of the same magnitude as for the US data.

For the Japanese market as shown in Panel B of Table 3 we also obtain similar average value weighted market returns, with 0.16% for the FF data and 0.18% for our data. Also the correlation of the two series is high, amounting to 0.94.

[Table 3 here]

We next compile overall common risk factors. The results are also shown in Table 3. For the SMB and HML factors in Europe the average returns are also similar with -0.07% (FF data) versus -0.10% (our TRD and TRW data) for SMB and with 0.43% (FF data) versus 0.40 (our TRD and TRW data) for HML. The correlations for the two factors are a bit lower than for the US amounting to 0.84 respectively. The average returns for the WML are 0.89% for both datasets and the correlation is a bit lower than for the US, but also quite high, amounting to 0.91.

[12] We suspect that the low correlation of our indices with the comparison indices for Luxembourg, Slovakia, and Iceland can be explained by the fact that companies which have an influence on the respective local market returns are nevertheless so small that they are not sufficiently covered by TRD and TRW. For example, a closer examination reveals that over 50% (in terms of the market capitalization) of the SAX is not covered by TRD data when we try to find the corresponding companies in April 2001 (according to Bratislava Stock Exchange, 2001) within our TRD and TRW data. Most companies are not covered by TRW, others are covered by TRW, but TRD provides no market data or the stocks are excluded by one of our screens.

For Japan, the average SMB and HML returns are a bit more dispersed than for the US and Europe, but still point into the same direction (t-tests imply that SMB is not different from zero, whereas HML is different from zero for both datasets at all conventional significance levels). The average SMB return is -0.05% for the FF data and -0.14% for our data. The average return figures for HML are 0.50% (FF data) and 0.63% (our TRD and TRW data). The correlations are 0.88 (SMB) and 0.81 (HML). The average WML return is 0.06% for the FF data and 0.04% for our data. The correlation of the two series is 0.92. Our results are, thus, in line with earlier results that the momentum anomaly is non-existent in Japan (e.g. Asness et al., 2013; Fama and French, 2012).

In sum, this section provides additional confirmation of the quality of our dataset and shows that our common risk factors constructed with TRD and TRW data are similar to the FF counterparts for Europe and Japan, like in the previous sections for the US.

3. Size and profitability of momentum

We are now in a position to investigate the substantive questions that motivate this paper. First, we re-examine the much-debated size effect (Section 3.1). Second, we consider the interrelation of size and momentum (Section 3.2).

3.1. International size premiums

We consider two different approaches to detect a possible size effect: First, we calculate the SMB factor as described in Section 2.1 and Appendix A.2.1. Second, we build a long-short portfolio which is long in the smallest 10% of the stocks in the dataset and short in the biggest 10%. To check the robustness of the latter approach we employ equal breakpoints as well as breakpoints which mimic the NYSE breakpoints.

For the first approach we calculate the mean returns of the SMB factors and and report the corresponding t-statistics. Since factor risk premiums can be estimated by means when factors are excess returns (Cochrane, 2005, p. 231) this is one possibility to test for a size premium. Columns (1) and (2) of Table 4 display the results.[13] A positive mean return of the SMB factor is obtained for seven of the fourteen examined countries. However, none of these mean returns are significantly different from zero with the exception of the negative German SMB mean return. These results suggest that the size effect may have been eroded over time.

[Table 4 here]

However, the SMB factor portfolio is a relatively crude measure of size differences as it is based on only two size groups. Therefore, we examine in the second approach raw returns as well as four-factor alphas of more extreme spread portfolios. The idea that size effects may be found in more extreme quantiles of the distribution goes back to Banz (1981), Keim (1983) and Brown, Kleidon and Marsh (1983); Fama and French (1992) consider size deciles using NYSE breakpoints.

Two considerations play a role for examining extreme size effects in individual countries: which number of size groups to consider and where to set the breakpoints of the groups. We consider three variations: (1) a decile split with NYSE breakpoints, (2) a decile split with equal breakpoints, and (3) a quintile split with equal breakpoints.

In each case, we construct a portoflio short in the biggest group and long in the smallest group of stocks for each country. For example, in the case of the decile split with equal breakpoints, the four-factor alphas are calculated as the intercepts of a regression of the spread portfolio (the "1-10-spread") on the market, SMB, HML, and WML factors:

$$\left(r_t^1 - r_t^{10}\right) = \alpha + \beta_M * \left(r_{M,t} - r_{f,t}\right) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{WML} * WML_t + \varepsilon_t \qquad (1)$$

Where r_t^1 (r_t^{10}) is the return of the small (big) size decile in time t, $r_{M,t}$ is the return of the market portfolio in time t, $r_{f,t}$ is the riskfree rate proxy in time t, SMB_t, HML_t, and WML_t are the factors as

[13] We only report results with factors using approximate NYSE breakpoints (columns (1)-(6)) where enough stocks are available to conduct meaningful factors. For most of the countries not reported a portfolio sort into six portfolios – three BE/ME groups and two size groups indepently – would produce empty or poorly diversified (e.g. dominated by one or two stocks) portfolios at some points of the time series.

described in Appendix A.2.1, β_M, β_{SMB}, β_{HML} and β_{WML} are the corresponding factor loadings, α is the four factor alpha, and ε_t is an error term. Spread portfolios for the other two approaches are calculated similarly.

First, we present results for the 1-10 size spread portfolio which is based on (approximate) NYSE breakpoints (see Appendix A.2.2). This approach of constructing size deciles is akin to the approach of Fama and French (1992), who use NYSE breakpoints. The results for the raw returns are shown in columns (3) and (4) of Table 4. Nine out of fourteen countries show a positive size premium, and three of them (Australia, Canada and Hong Kong) are significant (5% level). The results for the estimated four-factor alphas are depicted in columns (1) and (2) of Table 5. As expected, correcting for the risk factors lowers the size premiums and also the t-statistics. Here, ten out of fourteen countries show a positively estimated size premium, but only the Canadian one is significant (5% level), whereas the UK size premium is significantly negative (10% level).

Second, we present the results for the 1-10 size spread with equal breakpoints. Columns (5) and (6) of Table 4 show that the size premiums are greater than zero for all countries except Italy and significant (10% level) for nine out of fourteen countries. The estimated four-factor alphas, shown in columns (3) and (4) of Table 5, are greater than zero for all countries examined and different from zero at the 10% significance level for nine out of fourteen countries.

[Table 5 here]

These results for *individual* countries complement those in De Moor and Sercu (2013) who find a decile-based size effect for an *aggregated* international dataset. The estimated 1-10 size spread from the Carhart model of 1.45% for the aggregated international dataset in De Moor and Sercu (2013) is close to the estimated US 1-10 spread of 1.46% in our country dataset, which is plausible given that US data probably has a significant influence on the aggregate international dataset.[14] Besides focusing on

[14] Our study (and the one by De Moor and Sercu (2013)) uses equal breakpoints for the creation of the 1-10 spread portfolio.

individual countries, another difference between our studies is that we use value weighted returns, whereas De Moor and Sercu (2013) use equal weighted returns.[15]

Third, we wish to consider a larger number of countries.[16] Therefore, we construct quintile instead of decile portfolios.[17] This approach allows us to examine nine additional countries. The results for the raw returns are shown in columns (7) and (8) of Table 4. Average returns of the quintile spreads have the same sign as the decile spreads (with Italy as the exception) and the magnitude of the average returns is in general lower than for the decile spreads. All but the Belgian premiums are positive and seven out of 23 country premiums are significant (10% level). In Table 5 we report results for two different versions of the factors to estimate four-factor alphas. Columns (5) and (6) show estimated four-factor alphas of the size quintiles for the countries examined before with factors constructed using approximate NYSE breakpoints, as before. The results are again very similar to the decile results with equal breakpoints. All but the UK size premiums are positive and eight out of fourteen country premiums are significant (10% level). Columns (7) and (8) shows the estimated four-factor alphas of the size quintiles with factors constructed using equal breakpoints. For the additional nine countries all estimated size premiums (except for Poland) are positive and two of them are significant (10% level). Overall out of twenty-three countries twenty-one estimated size premiums are positive and ten of them are significant (10% level).

Overall, these results show that size premiums, when they exist, are driven by the smallest 10-20 percent of stocks and that there are considerable differences across countries. We note that the returns from these strategies appear to be rather substantial. In particular the returns for the 1-10 spread with equal breakpoints are up to 3.51% per month in the case of Australia, which is about 51% annually. Other major markets like the US, France, or Canada also show huge returns with 1.45%, 1.30%, and 3.08%

---

[15] Fama (1998, p. 296) makes the case for using value weighted returns. He argues that value weighted returns capture more accurately the total wealth effects experienced by investors. Furthermore, he is concerned that using equal weighted returns may amplify model problems. Novy-Marx and Velikov (2014) are also concerned about the use of equal weighted portfolios. They argue that equal weighted portfolio strategies have generally two to three times higher transaction costs and are therefore often less profitable to implement (p. 3).

[16] Deciles – whether with NYSE breakpoints or equal breakpoints – are unsuitable for this. For example, the number of Irish stocks is around 30-60 over the examined time period. Using the approach with approximate NYSE breakpoints would, therefore, imply that in the big size group there are around 1-3 stocks. This portfolio would be often dominated by one firm; or even be empty for some time period. Even with equal breakpoints this portfolio would contain only three to six stocks. The 1-10 spread would therefore depend very much on 1-3 big firm(s), if it is even computable (and therefore not empty) for the time span considered. In addition, a similar, even worse, problem is present in case of the factor construction for these smaller countries.

[17] The quintile sorts are also based on equal breakpoints.

(19%, 17%, and 44% annualy). By way of comparison, the market excess return for the US is about 0.57% (7% annually) over the same period. The returns for the 1-5 spreads are smaller, but still a few countries beat the US market excess return.

The results discussed above reveal a huge difference between the approaches using approximate NYSE breakpoints and equal breakpoints. The reason for this is that the composition of the respective portfolios of theses approaches is very different. For the case with approximative NYSE breakpoints for the US the small (big) portfolio is composed of the 45% (4%) of the smallest (biggest) stocks, whereas it is composed of the 10% (10%) of the smallest (biggest) stocks in case of the equal breakpoints .[18] Therefore, the small portfolio in the case with equal breakpoints is dominated by rather tiny stocks. For example, Fama and French (2008, p. 1654) point out that microcaps (stocks below the 20th NYSE percentile – which would roughly correspond to the 60th percentile of our overall sample) account for only 3% of the market cap of the NYSE-Amex-NASDAQ universe. The results with equal breakpoint should, therefore, be treated with caution. Using equal breakpoints exacerbates the problems associated with equal weighted portfolios as discussed by Fama and French (2008, p. 1654).

So far, our analysis does not explicitly show whether the significant size premiums, are in fact exploitable are not. On the one hand, Fama and French (2008) argue that „*...if the extreme returns associated with an anomaly variable are special to microcaps, they are probably not realizable because of the high costs of trading such stocks*" (p. 1655). Indeed, we find most of the "action" in extreme size quantiles, suggesting that a trading strategy may be difficult to implement. On the other hand, Frazzini et al. (2012) document that for a smart investor real-world transaction costs – also in international markets – in traditional trading strategies (including size) are an order of magnitude smaller than typically believed. We address the question of practical implementability explicitly in Section 4.2.

[18] See Table A.12.

3.2. International size and momentum portfolios

3.2.1 Contribution to the literature

In contrast to the size premium as such, the question of the interplay of size and momentum has received rather little attention so far. This is surprising given the enormous importance of the momentum strategy in practice. The only major studies we are aware of that address the interplay of size and momentum are Jagadeesh and Titman (1993), Hong et al. (2000), and Israel and Moskowitz (2013). Jegadeesh and Titman (1993) form three size groups and examine whether the profitability of momentum strategies is confined to particular size groups. They find that this strategy works for all three size subgroups. Hong et al. (2000) sort stocks on size and momentum to test the underreaction hypothesis of Hong and Stein (1999). This hypothesis holds that information spreads with different speed for different asset classes and that asset classes with slower diffusion of (firm-specific) information exhibit more pronounced momentum. One prediction of Hong et al. (2000), therefore, is that smaller stocks have a higher momentum premium than bigger stocks. Their central finding is that "*once one moves past the very smallest capitalization stocks (...) the profitability of momentum strategies declines sharply with market capitalization*" (p. 267). Israel and Moskowitz (2013) examine the momentum spreads of each of the the five size groups from the 25 portfolios provided by Kenneth French. They do not find support for the results in Hong et al. (2000), but rather observe that "*momentum premia are present in every size group*" and they "*find no consistent evidence that momentum returns decrease with firm size*" (p. 295). They argue that the main reason for the difference of these results and the results of Hong et al. (2000) is the considered time period.

All three studies use CRSP data for the US. The time period of Jagadeesh and Titman (1993) is 1965-1989, the time period of Hong et al. (2000) is 1980-1996, and the time period of Israel and Moskowitz (2013) is 1926-2011. The dataset used in this paper is for several countries (including the US) and is from 1991 to 2012 (individual time periods for the different countries are indicated in the table captions).

Our analysis, therefore, constitutes an out-of-sample analysis regarding the time span, country coverage, and data source. In addition to the momentum premiums across different size groups, we also examine the size premiums across different momentum groups.

3.2.2 Momentum conditional on size

We sort by size and momentum jointly (three-by-three) and construct long-short portfolios for each size as well as momentum group. As described in Section 3.1, we examine raw returns as well as four-factor alphas of winner-loser momentum spread portfolios and small-big size spread portfolios to judge whether there is a momentum/size effect conditional on size/momentum.[19]

The results of the momentum premiums conditional on size for the raw returns are shown in Table 6. High momentum returns generally occur in every size group, but there are considerable differences across the different countries. Most often the biggest momentum premiums are located in the middle size group (eight countries) followed by the biggest size group (four countries) and only for two countries the momentum premium is biggest in the small size group.

Judging the central prediction of Hong et al. (2000) for these results is tricky. A monotonic relationship between size and momentum where momentum premiums decrease with size is only observable for Italy and the Netherlands. However, the returns of the middle size group are bigger than the returns of the big size group for eleven out of fourteen countries (see column (7)). For the US, we reject the null hypothesis of no difference between the middle long-short portfolio and the big long-short portfolio returns with a t-statistic of 2.06 at the 5% significance level (see column (8)). In total for six (five) countries the difference of the returns is positive and significant at the 10% (5%) level.[20] The

[19] Differing from Jegadeesh and Titman (1993) and Hong et al. (2000), we do not use the six-month/six-month strategy, but use the previous 12 months with skipping the most recent one for predicting the returns of the next month, like we did with the construction of the momentum factor in Appendix A.2.1 (and is also done in Israel and Moskowitz, 2013).

[20] These results are similar to the results of Israel and Moskowitz (2013), but differ in conclusion. Israel and Moskowitz (2013) split the long-short momentum returns into five groups, from small to big stocks. They use CAPM alphas and test if the difference of the smallest and the biggest long-short portfolio returns is significant. They cannot reject the null hypothesis for the US with a t-statistic of 1.56. They use a sample period from 1927 to 2011. We instead split the long-short momentum returns into three groups, from small to big stocks. Here, we use raw returns (four-factor alphas are discussed in the following) and test if the difference of the middle long-short portfolio and the big long-short portfolio returns is significant. (Using one of the three middle

countries for which the differences are significant at the 5% level include major markets like the US, UK, Germany, and France. On the other hand one of the four countries (Japan) where the prediction of Hong et al. (2000) fails is a known excpetion and two of the other countries have a rather small stock market (Denmark and Norway). These results do not seem to be particular to our specific time period and the result is qualitatively the same if we consider different countries (results are not reported, but are available on request).

In sum, we consider these findings on international stocks as (modest) evidence in favor of the prediction of Hong et al. (2000).

The results of the momentum premiums conditional on size for the estimated four-factor alphas are shown in Table 7. It is remarkable that most of the estimated momentum premiums in the biggest size group (columns (5) and (6)) are negative (twelve out of fourteen) and some are even significantly negative (five at the 10% level). Moreover, the central prediction of Hong et al. (2000), that the momentum premium decreases (sharply) when moving from medium size to big size stocks, is confirmed by our international dataset for all but one country (Japan), as shown in column (7). Moreover, for eleven (ten) of theses countries this difference is significant at the 10 % (5%) level.

We interpret these results to be in line with the results of Chui et al. (2010), who suggest that momentum is related to individualism.[21] The individualism measure of Chui et al. (2010) is indeed highly correlated with our average momentum returns across countries. We get cross-country correlations of the average momentum returns of the small, medium, and big size groups with the static individualism measure according to Hofstede (2001) as high as 0.19, 0.52, and 0.56. The correlation coefficients with the four-factor alphas are a bit lower with 0.10, 0.24, and -0.07.[22] This suggests that individualism may be connected to average momentum returns for middle size and also for big stocks (when no risk-adjustment

portfolios, or a combination thereof, instead of the smallest portfolio in case of the Israel and Moskowitz (2013) study would most probably not change the results, since the returns and t-statistics of the four smallest long-short portfolios are very close to each other.) Our sample period is generally from 1991-2012 (exceptions are indicated in Table 6). Given the differences in the considered sample period and methodology we consider the difference in the t-statistic as rather small (1.56 vs. 2.06), though the conclusion of the two studies is different.

[21] Chui et al. (2010) suggest that momentum profits are driven by behavioral biases, like overconfidence or self-attribution. Namely, they relate cross-country cultural differences to momentum. These differences are measured by a static individualism measure proposed by Hofstede (2001). They find that the individualism measure is positively associated with momentum profits.

[22] We use the values of the individualism index reported in Table 1 of Chui et al. (2010) and the average momentum returns and alphas reported in Tables 6 and 7.

is undertaken), but to a lesser extent for small stocks.

[Table 6 here]

[Table 7 here]

3.2.3 The role of shorting

Avramov et al. (2013) argue that momentum strategies derive their profitability from shorting loser stocks in the first place. They argue that this observation is mainly driven by high credit risk firms that experience deteriorating credit conditions. Table 8 reports the raw returns in excess of the risk free rate for the nine portfolios jointly sorted on size and momentum. This table provides limited support for the Avramov et al. (2013) findings. For the smallest size group the short position (column (1)) never contributes sustantially to the momentum premium and often lowers it considerably. Intrestingly, always taking the long position in winners for small stocks gains a positive premium, which is always significant, with the exception of Japan. For medium size stocks the results are more mixed, but still there is only one country for which the short positon contributes significantly to the momentum premium (Germany). Taking always the long position in winners for medium size stocks also leads to a positive premium for all countries. Among those, eleven are significant (5% level). For big stocks the picture is similar as for medium size stocks. The portfolio return of the presumed short position in losers (column (7)) itself is never significantly different from zero and all but one long position for winner stocks is positive and ten are significantly different from zero (10% level).

For the estimated risk-adjusted returns, shown in Table 9, the results are a bit different. For the small stocks the picture is similar as for the raw returns. The estimated alphas of the presumed long position in winners are always positive and significantly different from zero (10% level). The estimated return of the presumed short position in losers is only negative and significantly different from zero for the

Netherlands. For the medium size stocks the results are mixed and losers as well as winner stocks contribute to the momentum premium. For the big size stocks there is no sizeable estimated positive momentum premium and also no sizeable estimated contribution from either the long or the short position.

In sum, we do not find consistent support for the arguments of Avramov et al. (2013), but rather find evidence that long positions of raw returns gain substantial returns.

[Table 8 here]

[Table 9 here]

3.2.4 Size conditional on momentum

The results of the raw return for the size premiums conditional on momentum are shown in Table 10. Among winner stocks there seems to be a size premium across most countries. All but one small-big size premiums (columns (5) and (6)) are positive, and eight of them are significant (5% level). Occasionally there also seems be a size premium for some countries when momentum is medium. For loser stocks there is also sometimes a size premium, but there are also countries where the size premium is around zero and countries where the size premium is negative.

Results of the estimated four-factor alphas for the size premiums conditional on momentum are shown in Table 11. Strikingly, among winner stocks there seems to be a size premium across all countries. All estimated small-big size premiums (columns (5) and (6)) are positive, and all but one are (largely highly) significant. The results for the loser and medium momentum groups are similar to the raw returns and sometimes the estimated premiums are positive and significant and less frequent around zero or slightly negative.

[Table 10 here]

[Table 11 here]

In addition, we also examined the conditional size premiums for different subperiods (1991-1999 and 2000-2012) and found the results to be quite stable across these subperiods (results are not reported, but are available on request).

3.3 Summary

The returns of the momentum-based strategies are quite large, but not as sizeable as for some size returns in Section 3.1. For example, the medium momentum returns are, apart from two exceptions (Japan and Singapore), for most countries about 1% per month (13% annually), but sometimes even higher, up to 1.80% per month for Australia (24% annually). This is also much bigger than the market excess return of the US. For the size strategies, conditionally on momentum, the results are not as uniform as for the momentum strategies conditionally on size, but still there are big returns for some countries. For example, the Canadian size strategies earn between 2.26% and 5.55% per month (between 30% and 90% annually). As was the case with the size strategies described earlier, the question to be addressed below is whether these strategies are implementable once trading costs are taken into account.

Overall, our results imply a positive and sizeable momentum premium especially for medium size stocks and a positive and sizeable size premium especially for winner stocks for most countries.

4. Size and momentum when adjusting for trading costs

In this section we expand the analysis of Section 3 with a view towards the actual implementability of the strategies. To do so we apply three different approaches, described in Section 4.1. The first one utilizes the average trading costs from Frazzini et al. (2012). The second one does not assume any trading cost a priori, but computes implicit "critical trading" costs that one could bear and still obtain marginally significant results with the assumed trading strategies. Third, we calculate the monthly trading volume of the portfolios examined, to assess whether it is possible to realize such strategies without too much price impact (which would drive the trading cost beyond the numbers assumed for the two approaches described above).

4.1. Trading costs and trading volume

Our first approach to take trading costs into account builds on the work by Frazzini et al. (2012). In contrast to prior work (e.g. Lesmond et al., 2003) which focuses on average trading costs for an average investor, Frazzini et al. (2012) are interested in the trading costs of a large arbitrageur. The authors use a propriary dataset of live trading data from a large institutional money manager and estimate trading costs by comparing theoretical trades with trades actually excuted, thereby being able to apply the implemementation shortfall approach (Perold, 1988). Implementation shortfall is a relatively general measure of trading costs, which accounts for the bid-ask spread, market impact, commissions, and other components (Frazzini et al., 2012, p. 13). Frazzini et al. (2012, Table A5) report market impact measures (which are similar to implementation shortfall) for different time periods and different size groups. Drawing on their work, we, therefore, use 30 basis points as trading costs for all small stocks before 2001 and 40 basis points from 2001 on. For big stocks we use 15 basis points as trading costs for the whole time period.

We calculate the return r_t^{tc} for a long-short portfolio after trading costs as follows:

$$r_t^{tc} = r_t - tc^l \cdot to_t^l - tc^s \cdot to_t^s \quad (2)$$

where r_t is the portfolio return before trading costs in time t, tc^l (tc^s) denotes the trading costs of the long (short) portfolio, and to^l_t (to^s_t) is the portfolio turnover of the long (short) in time t. Trading costs of a portfolio are the result of portfolio turnover (stocks bought plus stocks sold in percentage of portfolio volume) times average trading costs. We apply this correction to all portfolios considered as well as to the portfolios used to construct the factors. This approach is only an approximation of the actual trading costs since we use fixed values and not an actual trading cost function like Frazzini et al. (2012). Given the constraints on available data, we consider this nevertheless as a useful excersise, especially in conjunction with our other tests, described in what follows.

In our second approach to assess the relevance of trading costs, we define what we call "critical trading costs". The critical trading costs are the maximal trading costs that an investor can afford for a given spread portfolio so that the portfolio return is still (marginally) positive at a certain significance level. We define the average critical trading costs tc_{crit} as:

$$tc_{crit} = \frac{\frac{1}{T}\sum_{t=1}^{T} sp_t - t_{crit}\sqrt{\frac{1}{T}\sum_{t=1}^{T}(sp_t-\mu)^2}}{\frac{1}{T}\sum_{t=1}^{T} to_t} \tag{3}$$

where T is the number of periods, t_{crit} is the critical value of the assumed t-test (typically 1.64, 1.96 or 2.58 for 10%, 5% or 1% significance levels), sp_t is the return of the spread portfolio with mean μ in time t, and to_t is the portfolio turnover in time t, as before. If the spread portfolio is long in small and short in big stocks, we still posit that the average trading costs of a big stock are 15 basis points. Since big stocks are more liquid than small stocks (e.g. De Moor and Sercu, 2013, Table 1), we believe this assumption is appropriate. When the long and short portfolios are averages of other portfolios, as it is the case with the SMB, HML, and WML factors, the portfolio turnover is also an average of the respective portfolios.

Third, we calculate the monthly US dollar trading volume for each portfolio. This provides another way to assess whether the strategies under consideration actually work or may be infeasible due to illiquidity constraints. To calculate the US dollar trading volume we take the TRD variable 'turnover by volume' (VO), which represents the adjusted amount of shares traded per month and multiply it by the 'price' (P) variable converted into US dollars. Using the last price of each month and multiplying it by all traded shares of the whole month is an approximation. The exact approach would be to use the price for each transaction that was actually paid. However, we believe that this is not a crucial problem. A specific challenge can arise in the context of adjustments for corporate events. TRD calculates monthly figures from daily ones by summation, and hence sometimes mixes-up adjusted and non-adjusted figures, if these figures change whithin a given month. Therefore, we search for each country for the biggest two volume figures on the stock level and exclude these stocks completely if these high numbers seem inaccurate.[23,24]

4.2. *International size premiums*

This section repeats the analysis of Section 3.1, but now accounting for trading costs using the three methods described in Section 4.1.

4.2.1 *Trading cost-adjusted results*

Since the mean return of the SMB factor and the premium from a 1-10 spread based on NYSE breakpoints are mostly insignificantly different from zero, the trading cost-adjusted results are virtually the same as in Section 3.1 (results are not reported, but are available on request). For the 1-10 spread with equal breakpoints we see some changes. While in Section 3.1 nine premiums are significant, now six of them remain significant (10% level). For the 1-5 spread six of the seven significant premiums in section 3.1 remain significant (10% level). For the estimated risk-adjusted returns, the results are quite similar to the results of Section 3.1 (results are not reported, but are available on request). For some countries the estimated four-factor alphas and t-statistics are even slightly higher.

4.2.2 *Critical trading costs*

Table 12 shows critical trading costs as described in Section 4.1. We only report positve values since negative values have no meaning in this context. Thus, naturally, for the SMB return the critical trading

[23] Unlike with return data these errors are not limited to small stocks. We also exclude rather big stocks such as Vodafone and Royal Dutch Shell in the UK. Since providing clean US dollar volume data is not the main focus of this paper we belive that this practice is appropriate and has little effect on the overall results.

[24] To check if the US dollar volume data calculated this way are reasonable, we aggregated the TRD data for some of the countries under consideration and compared it with the aggregated US dollar volume data provided by the World Federation of Exchanges (WFE, http://www.world-exchanges.org/statistics). For most countries examined the US dollar volume data match up nicely. However, for Germany the figures are very different: the data from the WFE report a mean value of US$148.67 billion for the period from 02/2002 to 12/2011 whereas the aggregated TRD data report a mean value of US$4.60 billion. Therefore we omit Germany from the sample in this case.

costs are never positive (because even before trading costs the returns are not significantly different from zero). For the 1-10 spread with NYSE breakpoints three countries have positive critical trading costs: Australia, Canada, and Hong Kong. These countries have also the biggest critical trading costs for the 1-10 and 1-5 spreads with equal breakpoints. Other countries with notable trading costs for the 1-10 spread with equal breakpoints are France, Japan, the US, and to a lesser extent Germany, Norway, and the UK, for which the trading costs at the 10% significance level are smaller than the 40 basis points imposed in the exercise above. For the 1-5 spread the critical trading costs are often less then for the 1-10 spread but with the exception of Germany, Japan, the UK, and the US the countries with notable critical trading costs are the same. For the newly added countries, Greece has the highest critical trading costs, almost as big as for Hong Kong. Ireland has also positive critical trading costs, for all other newly added countries the critical trading costs are negative. Note that the critical trading costs are partly really large, consistent with the fact that for some strategies the spread returns found in the absence of trading costs were highly significant. Consider, for example, the 1-10 spread with equal breakpoints for Australia: the critical trading costs are more than 2000 basis points, more than fifty times of the trading costs imposed above. Also, trading costs for France are in this case still big, with about 20 times as imposed earlier.

Overall the results are strongest for the 1-10 spread with equal breakpoints where we report for about two-thirds of the countries positive trading costs. For the 1-5 spread with equal breakpoints this number diminishes to about one-third (both holds for the 10% significance level). However, if one imposes a 5% significance level only about one third of the countries for the 1-10 spread show positive trading costs and only about one fifth for the 1-5 spread.

[Table 12 here]

4.2.3 Trading volume and market depth

In Tables 13 and 14 we report the average portfolio turnover of the long and short portfolio of the 1-

10 and 1-5 spreads, respectively. Besides the NYSE and equal breakpoint versions we also differentiate between the (monthly) portfolio turnover over the whole year and the portfolio turnover in July, when the portfolio is yearly rebalanced.[25,26]

Over the whole year the average portfolio turnover of the small (big) portfolio in 1-10 spread with NYSE breakpoints, the turnover is about 70% (22%) on average.[27] The July values are about the same magnitude but a bit lower, with about 60% for the small and 15% for the big stocks on average. For the case with equal breakpoints the turnover values for the big portfolio are slightly lower (about 18% yearly and about 10% for July) and considerably higher for the small portfolios with about 156% (yearly) and 130% July).[28] The average turnover for the portfolio of small stocks is in both cases with equal breakpoints very high, in most cases half of the portfolios have to be exchanged per year. Therefore, the results really depend upon trading costs of 40 basis points for small stocks. If trading costs due to illiquidity are much higher, excess returns will be much lower.

[Table 13 here]

[Table 14 here]

Tables 13 and 14 also report average US dollar trading volumes of the 1-10 and 1-5 spread strategies, respectively. The average US dollar trading volumes for the small size portfolio with NYSE breakpoints range from US$38 million for Denmark to US$3,815 million for the US, in July (see column 5). The average US dollar trading volumes for the big size portfolio with NYSE breakpoints are much bigger and range from US$3 billion in Denmark to US$1,090 billion in the US (column 6). Therefore, the average US dollar trading volume of the big size portfolio is for all countries at least ten times as high as for the

---

[25] Note that July values are effectively the yearly turnover values, since the portfolio is rearranged every July. Average monthly turnover values, using all observations are reported for comparison purposes with the size/momentum portfolios.
[26] Tables 13 and 14 use only July values; for numbers of the overall dataset see Tables A.23 and A.24.
[27] Tables A.23 and A.24 report turnover values on a monthly basis. We multply these values by 12, so they can be compared with the July values.
[28] The corresponding numbers for the 1-5 spread in Tables 14 and A.34 are between those two extreme cases.

small portfolio and often hundred times as high or even higher. We do not discuss the results for all monthly observations because they are similar to the results using July figures.[29]

We now turn to the results with equal breakpoints for July, reported in columns (7) and (8) of Table 13. The average US dollar trading volume of the small size portfolios are now much smaller, ranging from below US$2 million to US$376 million. The average trading volume of the big size portfolio is, therefore, slightly higher, ranging from US$4 billion (Denmark) to US$1,400 billion (US). The average US dollar trading volume for the small quintile portfolios, shown in column (3) of Table 14 is higher, but still not impressive, ranging from US$3 million (Ireland) to US$805 million (US). For the big quintile portfolio, in column (4), these values range from US$2 billion (Poland) to US$1,600 billion (US).

To combine the previous results, we proceed in three steps. First, we have to determine what a reasonable portfolio or fund size for a large arbitrageur should be. Second, we determine the maximum fund size for our portfolio. Third, we set this into relation with the turnover volume of a large arbitrageur.

First, Frazzini et al. (2012, Table 6) report implied fund sizes between US$1.5 billion and US$15 billion for the US. We assume that a fund should have at least a size of US$1.5 billion to be incepted.

As a second step, to compute the average maximum fund size, we utilize information on turnover and trading volume from Table 13. Consider first the case of the size portfolios with NYSE breakpoints from Table 13. For the US, for example, the avarage monthly turnover in July of the small size portfolio is 74% (Table 13, column (1), last row). If we assume that we invest in all available small size stocks in the US (with the proportions according to our value weights) we trade stocks with a volume of US$3.8 billion each July on average (Table 13, column (5), last row). Thus, we can conclude that the average maximum fund size (the 100%) is US$3.8 billion / 0.74 ≈ US$5 billion. Assuming that the hypothetical fund of US$1.5 billion is equally divided between small and big stocks, we end up with a small size portfolio of about US$750 million. This is about 15% of the maximum fund size.

For the third step, to set this into relation with the turnover volume of a large arbitrageur, we are interested which fraction of the market can be traded under the assumptions made by Frazzini et al.

[29] See Table A.23 for detailed numbers.

(2012). Frazzini et al. (2012, Table 1, Panel B) report that for their overall trading data they move a fraction for about 1% of the daily trading volume. Assuming that this is the same on a monthly level, we conclude that the price impact of the size strategy examined here is likely higher.

When we perform the same exercise for the size portfolios with equal breakpoints, we get a maximum fund size of about US$250 million for the US.[30] This is less than the US$750 million required to compile the long-short portfolio. Therefore, even when we buy all suitable small size stocks available, we could only compile a fund with US$500 million (which is double the US$250 million, since the long position is assumed the be same amount) for the US. If we do so, however, we would have a very high price impact and trading costs will rise by a large amount.[31] The same problem occurs for the 1-5 spread where the maximum fund size is about US$700 million for the US.

Turning to the other countries, this problem is slightly less pronounced, since the fraction of trading volume for small to big stocks is higher for most of the other countries, compared to the US. However, the cumulated maximum fund sizes for the other countries are at best about 2.5 times as much as for the US (this is for the 1-5 spread, where we added additional countries), and, therefore, still rather small.

In addition we can also calculate the overall trading costs resulting from theses strategies. We do this simply by comparing the numbers from Section 3.1 with the numbers calculated in this section. For example the monthly overall trading costs of the equal weighted 1-10 spread for the US are 1.45% - 1.41% = 0.04 % which are about 0.48% on a yearly basis.

4.2.4 Summary

In sum, we find evidence for a size premium in a long-short strategy which is long in the very small stocks consisting of the smallest 10% of all stocks and short in the biggest 10% of all stocks, for most of the countries examined, even after correcting for transaction costs. However, we doubt that these

---

[30] The avarage monthly turnover in July of the small size portfolio in the US is 154% (Table 13, column (3), last row). If we assume that we invest in all available small size stocks (with the proportions according to our value weights) we trade stocks with a volume of US$376 million each July on average (Table 13, column (7), last row). Therby we can conclude that the average maximum fund size (the 100%) is US$376 million / 1.54 ≈ US$250 million for the US.

[31] For example, the literature on mergers and acquisitions report wealth increases of about 22% for target firms, this would imply a price impact much bigger than any of the critical trading costs reported above (e.g. Datta et al., 1992).

strategies are actually realizable since the US dollar trading volume of the smallest 10% of the stocks are really tiny. In principle, the same argument applies to the long-short strategy with the largest/smallest 20%. For this strategy the size premiums are smaller and the trading volume are bigger, but still rather tiny. We conclude that specific characteristics of microcaps, like their illiquidity, are responsible for (seemingly) economically sound excess returns. However, these excess returns are not exploitable by an active investment strategy.

4.3. International size and momentum portfolios

4.3.1 Momentum conditional on size

We apply the same analysis as in Section 4.2 to the size-momentum spreads discussed in Section 3.2.[32] Table 15 shows the trading cost-adjustedraw returns of the momentum strategies by size groups. Primarily, we observe positve momentum premiums for the middle size stocks (columns (3) and (4)). Here, all premiums except the Japanese one are positve and ten of them are significant (10% level). We also observe positive momentum premiums for the other two size groups, but only few of them are significant (six for the small stocks and three for the big stocks). For the estimated risk adjusted momentum returns by size groups, shown in Table 16, the biggest stocks show no noteworthy momentum premiums. However, for the middle size group there are still eight significant and positive premiums (5% level) and for the small size group there are six positive premiums (10% level). The differences between medium size stocks and big size stocks are similar as in section 3.2.2, as can be seen in columns (7) and (8) of the Tables 15 and 16.

[Table 15 here]

[Table 16 here]

[32] We applied the same analyses to the nine size-momentum portfolios. The results are available on request.

We also report critical trading costs for the momentum premiums. Table 17 shows the results. There are positive critical tradings costs in every size group. In the biggest size group (columns (5) and (6)) we observe three countries, namely Australia, Canada, and Denmark, for which the critical trading costs are substantially higher than the trading costs imposed in the previous tables. For the middle size group we observe about ten countries with such substantial critical trading costs. For the small size group we observe six countries with substantial critical trading costs. Note that the biggest of the critical trading costs shown here are much smaller than for the size strategies. However, the middle size group has much smaller trading costs in reality, so that the assumed trading costs of 40 basis points for each trade is probably much smaller for most of the stocks in that group.

[Table 17 here]

In Table 18 we show the average portfolio turnover of the nine portfolios sorted on size and momentum. The average monthly portfolio turnover for the loser and winner portfolios is between roughly 30% and 80%. Furthermore, in Table 19 we show the average monthly US dollar trading volume of the nine size and momentum portfolios. One can observe a large gap between the US dollar trading volume of the big stocks (columns 7-8) and the small stocks (columns 1-3). For example, for the US the big winner stocks show an average monthly trading volume of US$788 billion, whereas the small winner stocks show an average monthly trading volume of only US$537 million, about 1500 times smaller. The volumes for the middle size stocks are in between, but still substantially smaller than the big stocks.

We apply the same reasoning as for the size spreads above and calculate theoretical maximum fund sizes. We also use the US as an example. First, the maximum fund size for small stocks, implied by the small winner portfolio since it is smaller than the small loser portfolio, is about US$1,385 million, this is bigger than for the small size portfolio with equal break points, but still rather small. Therefore, the same problems occur as for the size porfolios. In addtion, the critical trading costs are much lower. Thus, an increasing price impact will rather quickly diminish the returns by a great deal.

For the medium size stocks, implied by the medium loser portfolio, we calculate a maximum fund size of US$20 billion. Given a fund size of US$1.5 billion an investor will have to move a little less than 10% of the market each month. If one is willing to belive that the induced price impact does not drive trading costs above 50 basis points on average, then this strategy is able to provide positive returns on average.

However, for the big stocks, implied by the big loser portfolio, the maximum fund size would be about US$600 billion and, therefore, a fund with a size of US$1.5 billion, or even slightly bigger should be tradeable without too much price impact. However, we observe only for Australia, Canada, and Denmark strong results in favor of a momentum premium for this strategy.

In sum, momentum premiums for small stocks are likely not realizable because of a small market depth. Momentum premiums for medium size stocks are most likely feasible, though we can not rule out that part of the returns are diminished due to price impact. Momentum premiums for big stocks are only observed for raw returns and are only substantial for a few countries.

[Table 18 here]

[Table 19 here]

4.3.2 Size conditional on momentum

In addition, we also perform the same analysis for the long-short porfolios of size strategies conditionally on momentum. Essentially these strategies seem to work particularly well for four countries across all momentum classes: Australia, Canada, Hong Kong, and the US. This applies to raw returns, estimated four-factor alphas, and critical trading costs (results are not reported, but are available on request). However, in the end these strategies depend on the liquidity of the small size porfolio and, therefore, run into the same problems as the size strategy and the momentums stragegy for small stocks (see Tables 18 and 19 for the respective portolio turnover and the US dollar trading volume of the involved porfolios).

As we did with the size strategy we can also calculate the overall trading costs resulting from momentum/size strategies. We compare the numbers from Section 3.2 with the numbers calculated in this section. As an example, we considert the small momentum spread for the US (see Tables 6 and 15). The monthly overall trading costs are 0.68% - 0.23% = 0.45 %, which is about 5.54% on a yearly basis. For comparison Mitchell and Pulvino (2001, p. 2136) report yearly overall trading costs of 5.71%. Since we apply a long-short strategy and Mitchell and Pulvino (2001) persue a long-only strategy, our trading costs are about half as large.[33] Note that the transaction costs of the strategies examined here are about ten times bigger than for the size strategy. The main reason for this difference is that the momentum portfolios are rearranged every month which results in a really high portfolio turnover, whereas the size portfolios are rearranged only once a year.

In sum, we find that profits from the here discussed strategies are most likely possible for the momentum strategy of medium size stocks. All other strategies either earn to little or have a marginal market depth.

5. Conclusion

Can investors profitably implement size and momentum strategies in international stock markets? What is the interplay between the two strategies? To answer these questions, we first construct a novel, replicable dataset and common risk factors from Thomson Reuters Datastream (TRD) and Thomson Reuters Worldscope (TRW) data. As a methodological contribution, we provide appropriate screens and data filters by which the quality and the reliability of the data can be raised significantly.

We document several sets of novel empirical results. First, we show that an extreme size premium exists in several individual countries. Second, we confirm, out-of-sample, the observation previously

[33] The portfolio turnover of the Mitchell and Pulvino (2001) strategy is similar as the turnover of our strategy. The stocks in the portfolio examined by Mitchell and Pulvino (2001) have an average duration of about 2 months, which would be a monthly portfolio turnover of 50%. Our strategy has a portfolio turnover of about 65% (=(56%+76%)/2, see Table 18).

made by Hong et al. (2000) for US markets that the profitability of momentum strategies declines sharply with market capitalization. Moreover, we find that within winner stocks there exists a considerable size premium for almost all countries in our dataset.

Third, we incorporate trading costs in various ways into the analysis, therefore critically assessing how feasible it is to practically implement investment strategies based on size and momentum. When accounting for trading costs we find that all strategies involving size are probably not realizable because the US dollar trading volume of the small size stocks needed for implementation is too low and actually trading these stocks with appropriate quantities would presumably increase stock prices and decrease the profitability of these strategies significantly. For the momentum strategies which involve medium size and big stocks this problem is not that severe. In particular we document a momentum premium for medium size international stocks even after trading costs.

References

Ammann, M., Steiner, M., 2008. Risk Factors for the Swiss Stock Market. Swiss Journal of Economics and Statistics 144 1–25.

An, J., Ng, D., 2010. Long-Run Risks and Value Premium: The International Evidence. Working Paper, Cornell University.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2008. High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence. Journal of Financial Economics 91, 1–23.

Artmann, S., Finter, P., Kempf, A., Koch S., Theissen, E., 2012. The Cross-Section of German Stock Returns: New Data and New Evidence. Schmalenbach Business Review 64, 20-43.

Asness, C., Frazzini, A., 2013. The Devil in HML's Details. Journal of Portfolio Management 39, 49–68.

Asness, C.S., Moskowitz, T.J., Pedersen, L.H., 2013. Value and Momentum Everywhere. The Journal of Finance 68, 929-985.

Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2013. Anomalies and Financial Distress. Journal of Financial Economics 108, 139–159.

Banz, R.W., 1981. The Relationship between Return and Market Value of Common Stocks. Journal of Financial Economics 9, 3-18.

Bauer, R., Cosemans, M., Schotman, P.C., 2010. Conditional Asset Pricing and Stock Market Anomalies in Europe. European Financial Management 16, 165-190.

Bratislava Stock Exchange, 2001. Monthly Statistics – July 2001.

Brown, P., Kleidon, A.W, Marsh, T.A., 1983. New Evidence on the Nature of Size-Related Anomalies in Stock Prices. Journal of Financial Economics 12, 33-56.

Brückner, R., Lehmann, P., Schmidt, M.H., Stehle, R., 2014. Fama/French Factors for Germany: Which Set Is Best? Working Paper, Humboldt University Berlin.

Campbell, J.Y., 1996. Understanding Risk and Return. The Journal of Political Economy, 104, 298–345.

Carhart, M.M., 1997. On Persistence in Mutual Fund Performance. The Journal of Finance 52, 57–82.

Chui, A.C.W., Titman, S., Wei, K.C.J., 2010. Individualism and Momentum around the World. The Journal of Finance 65, 361-392.

Cochrane, J.H., 2005. Asset Pricing, revised edition. Princeton University Press, Princeton. Datta, D.K., Pinches, G.E., Narayanan, V.K. 1992. Factors Influencing Wealth Creation from Mergers and Acquisitions: A Meta-Analysis. Strategic Management Journal 13, 67–84.

De Moor, L., Sercu, P., 2013. The Smallest Firm Effect: An International Study. Journal of International Money and Finance 32, 129–155.

Dimson, E., Marsh, P., 1999. Murphy's Law and Market Anomalies. Journal of Portfolio Management 25, 53–69.

Dimson, E., Nagel, S., Quigley, G., 2003. Capturing the Value Premium in the United Kingdom. Financial Analysts Journal 59, 35–45.

Eun, C.S., Lai, S., de Roon, F.A., Zhang, Z., 2010. International Diversification with Factor Funds. Management Science 56, 1500–1518.

Fama, E.F., 1998. Market Efficiency, Long-Term Returns, and Behavioral Finance. Journal of Financial Economics 49, 283–306.

Fama, E.F., French, K.R., 1992. The Cross-Section of Expected Stock Returns. The Journal of Finance 47, 427–465.

Fama, E.F., French, K.R., 1993. Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics 33, 3–56.

Fama, E.F., French, K.R., 1998. Value versus Growth: The International Evidence. The Journal of Finance 53, 1975–1999.

Fama, E.F., French, K.R., 2008. Dissecting Anomalies. The Journal of Finance 63, 1653–1678.

Fama, E.F., French, K.R., 2012. Size, Value and Momentum in International Stock Returns. Journal of Financial Economics 105, 457–472.

Ferreira, M.A., Keswani, A., Miguel, A.F., Ramos, S.B., 2013. The Determinants of Mutual Fund Performance: A Cross-Country Study. Review of Finance 17, 483–525.

Frazzini, A., Israel, R., Moskowitz, T.J., 2012. Trading Costs of Asset Pricing Anomalies. Working Paper, University of Chicago.

Gregory, A., Tharyan, R., Huang, A., 2009. The Fama-French and Momentum Portfolios and Factors in the UK. Working Paper, University of Exeter.

Griffin, J.M., 2002. Are the Fama and French Factors Global or Country Specific? The Review of Financial Studies 15, 783–803.

Hau, H., Lai, S., 2014. The Role of Equity Funds in the Financial Crisis Propagation. Working Paper, University of Geneva.

Heston, S.L., Rouwenhorst, K.G., Wessels, R.E., 1999. The Role of Beta and Size in the Cross-Section on European Stock Returns. European Financial Management 5, 9–27.

Hofstede, G., 2001. Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations across Nations, 2nd ed. Sage Publication, Beverly Hills, CA.

Hong, H., Stein, J.C., 1999. A Unified Theory of Underreaction, Momentum trading and Overreaction in Asset Markets. The Journal of Finance 54, 2143–2184.

Hong, H., Lim, T., Stein, J.C., 2000. Bad News Travel Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. The Journal of Finance 55, 265–295.

Horowitz, J.L., Loughran, T., Savin, N.E., 2000. Three analyses of the firm size premium. Journal of Empirical Finance 7, 143–153.

Hou, K., Karolyi, G.A., Kho, B.C., 2011. What Factors Drive Global Stock Returns? The Review of Financial Studies 24, 2527–2574.

Ince, O.S., Porter, R.B., 2006. Individual Equity Return Data from Thomson Datastream: Handle with Care! The Journal of Financial Research 29, 463–479.

Israel, R., Moskowitz, T.J., 2013. The Role of Shorting, Firm Size, and Time on Market Anomalies. Journal of Financial Economics 108, 275–301.

Jegadeesh, N., Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance 48, 65–91.

Keim, D.B., 1983. Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence. Journal of Financial Economics 12, 13-32.

Kothari, S.P., Shanken, J., Sloan, R.G., 1995. Another Look at the Cross-Section of Expected Stock Returns. The Journal of Finance 50, 185–224.

Leippold, M., Lohre, H., 2012a. Data Snooping and the Global Accrual Anomaly. Applied Financial Economics 7, 509-535.

Leippold, M., Lohre, H., 2012b. International Price and Earnings Momentum. The European Journal of Finance 18, 535-573.

Lesmond, D.A., Schill, M.J., Zhou, C. 2003. The Illusory Nature of Momentum Profits. Journal of Financial Economics 71, 349–380.

Liew, J., Vassalou, M., 2000. Can Book-to-Market, Size and Momentum Be Risk Factors That Predict Economic Growth? Journal of Financial Economics 57, 221–245.

Lo, A.W., MacKinlay, A.C., 1990. Data-Snooping Biases in Tests of Financial Asset Pricing Models. The Review of Financial Studies 3, 431–467.

MacKinlay, A.C., 1995. Multifactor Models Do Not Explain Deviations from the CAPM. Journal of Financial Economics 38, 3–28.

Mitchell, M., Pulvino, T., 2001. Characteristics of Risk and Return in Risk Arbitrage. The Journal of Finance 56, 2135–2175.

Nagel, S., 2001. Accounting Information Free of Selection Bias: A New UK Database 1953-1999. Working Paper, London Business School.

Newey, W.K., West, K.D., 1987. A Simple, Positive Semi-definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703–708.

Novy-Marx, R., Velikov, M., 2014. A Taxonomy of Anomalies and their Trading Costs. NBER Working Paper 20721.

Perold, A.F., 1988. The Implementation Shortfall: Paper vs. Reality. Journal of Portfolio Management 14, 4-9.

Rouwenhorst, K.G., 1998. International Momentum Strategies. The Journal of Finance 53, 267–284.

Schrimpf, A., Schröder, M., Stehle, R., 2007. Cross-sectional Tests of Conditional Asset Pricing Models: Evidence from the German Stock Market. European Financial Management 13, 880–907.

Schwert, G.W., 2003. Anomalies and Market Efficiency. In: Constantinides, G.M., Harris, M., Stulz, R.M. (Eds.), Handbook of Economics and Finance. Amsterdam, North Holland.

Van Dijk, M.A., 2011. Is Size Dead? A Review of the Size Effect in Equity Returns. Journal of Banking and Finance 35, 3263–3274.

Ziegler, A., Schröder, M., Schulz, A., Stehle, R., 2007. Multifaktormodelle zur Erklärung deutscher Aktienrenditen: Eine empirische Analyse. Schmalenbachs Zeitschrift für betriebswirtschaftliche Forschung 59, 355–389.

Table 1: Market returns and common risk factors for the US market

	FF			TR			
	Avg.	σ	t	Avg.	σ	t	ρ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VW	0.85	4.67	3.18	0.86	4.77	3.17	0.94
SMB	0.10	3.32	0.53	0.11	3.14	0.61	0.93
HML	0.25	3.14	1.40	0.28	3.28	1.50	0.88
WML	0.53	4.92	1.89	0.64	6.19	1.81	0.93

Note: This table reports descriptive statistics for the time series of monthly value weighted (VW) market returns as well as the returns of the SMB, HML and WML factors in %. We compare two different US datasets with each other: The FF and TRD and TRW (TR) as described in Section 2.1. We report the average (Avg.), the standard deviation (σ), the t-statistic (t) and the correlation coefficient between the two datasets (ρ). The t-statistic refers to the null hypothesis that the mean of the tested series is zero. The time period ranges from 07/1986 to 02/2012. All returns are in percent per month and are denominated in US$.

Table 2: Comparison with International Indexes

Panel A:	07/1989 - 06/2012					07/1999 - 06/2012				
	Avg.			ρ		Avg.			ρ	
	Com.	VW	EW	VW	EW	Com.	VW	EW	VW	EW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Australia (MSCI)	0.79	0.84	1.88	0.94	0.64	0.64	0.69	1.74	0.95	0.64
Austria (FTSE)	0.46	0.66	0.86	0.97	0.83	0.57	0.63	1.05	0.98	0.82
Belgium (BAS)	0.37	0.72	0.89	0.96	0.85	0.03	0.34	0.71	0.95	0.85
Canada (TT)	0.71	0.82	2.94	0.99	0.66	0.63	0.69	2.68	0.99	0.71
Denmark (FTSE)	0.74	0.79	0.83	0.97	0.71	0.87	0.81	0.77	0.98	0.76
Finland (FTSE)	0.84	0.85	1.08	0.97	0.71	0.32	0.48	0.92	0.99	0.70
France (CAC40)	0.62	0.67	1.22	0.98	0.75	0.19	0.33	1.40	0.99	0.78
Germany (FTSE)	0.54	0.64	0.78	0.98	0.77	0.41	0.36	0.75	0.98	0.79
Hong Kong (HS)	1.00	1.26	1.89	0.98	0.70	0.77	0.88	2.24	0.98	0.67
Ireland (ISEQ)	0.63	0.79	1.26	0.97	0.78	0.10	0.29	1.27	0.95	0.78
Italy (FTSE)	0.24	0.50	0.51	0.99	0.89	-0.11	-0.05	0.13	0.99	0.88
Japan (TOPIX)	-0.19	-0.15	0.32	1.00	0.84	-0.14	-0.09	0.60	1.00	0.80
Netherlands (AEX)	0.72	0.76	0.88	0.98	0.84	0.06	0.20	0.63	0.99	0.86
Norway (FTSE)	0.65	0.94	1.24	0.98	0.83	0.93	0.97	1.11	0.98	0.83
Portugal (MSCI)	0.47	0.64	1.21	0.94	0.76	-0.10	0.24	1.16	0.96	0.70
Singapore (MSCI F)	0.67	0.67	1.20	0.87	0.76	0.56	0.63	1.09	0.95	0.78
Spain (FTSE)	0.44	0.71	0.78	0.99	0.84	0.19	0.15	0.44	0.98	0.79
Sweden (FTSE)	0.88	1.04	1.21	0.97	0.79	0.68	0.69	1.16	0.99	0.80
Switzerland (SPI)	0.72	0.80	0.79	0.99	0.82	0.22	0.29	0.71	1.00	0.82
Turkey (MSCI)	4.63	4.44	5.79	0.88	0.88	2.50	2.56	3.52	0.97	0.90
United Kingdom (FTSE)	0.74	0.75	0.79	1.00	0.73	0.34	0.38	0.76	1.00	0.73

Panel B:	07/1989 -02/2012					07/1999 - 02/2012				
United States (RUSSELL)	0.82	0.83	3.10	1.00	0.69	0.37	0.40	4.24	1.00	0.74

Table 2 (continued): Comparison with European Indexes

Panel C:	01/1992 - 06/1999					07/1999 - 06/2012				
	Avg.			ρ		Avg.			ρ	
	Com.	VW	EW	VW	EW	Com.	VW	EW	VW	EW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	8)	(9)	(10)
Luxembourg (MSCI/LSE)	1.04	1.66	1.75	0.63	0.54	0.22	0.61	0.87	0.78	0.71
Panel D:	03/1992 - 06/2012									
Greece (MSCI)	0.21	0.37	1.27	0.93	0.67	-0.95	-0.80	0.06	0.94	0.68
Panel E:	02/1993 - 06/2012									
Poland (WGI)	2.26	1.97	2.72	0.92	0.85	0.82	0.72	1.47	0.99	0.85
Hungary (BUX)	1.75	1.69	2.28	0.98	0.80	0.89	0.66	1.81	0.99	0.60
Hungary (MSCI)						0.80	0.66	1.81	0.99	0.60
Panel F:	08/1996 - 06/2012									
Czech Republic (FTSE)	0.93	0.97	1.06	0.98	0.67	1.18	1.11	1.41	0.98	0.62
Panel G:										
Slovakia (SAX)						0.75	1.44	2.31	0.68	0.61
Panel H:						01/2001 - 06/2012				
Iceland (ICEXALL)						0.17	1.06	1.09	0.69	0.48

Note: In this table we report basic descriptive statistics of TRD calculated value weighted (VW) and equal weighted (EW) market returns and compare these indexes with publicly available indexes (denoted as Com.). For most countries we report two different time periods: a long one, typically ranging from 07/1989 - 06/2012 and a short one, typically ranging from 07/1999 - 06/2012, exceptions are indicated. We use the following country-specific indexes for comparison: MSCI (Australia, Portugal, Turkey, Luxembourg, Greece, Hungary), FTSE (Austria, Denmark, Finland, Germany, Italy, Norway, Sweden, United Kingdom, Czech Republic), Brussels All Share (BAS, Belgium), S&P/TSX composite index (TT, Canada), CAC40 (France), Ireland SE Overall (ISEQ, Ireland), Tokyo SE (TOPIX, Japan), AEX (the Netherlands), MSCI Free (MSCI F, Singapore), Madrid SE General (IGBM, Spain), Swiss Performance Index (SPI, Switzerland), Russell 3000 (RUSSELL, USA), Hang Seng (HS, Hong Kong), Luxembourg SE General (LSE, Luxembourg), The Share Index of the Budapest Stock Exchange (BUX, Hungary), Warsaw General Index (WGI, Poland), Slovak Share Index (SAX, Slovakia), OMX Iceland All Share (ICEXALL, Iceland). We report the average return (Avg.) and the correlation coefficient between the returns of the two datasets (ρ). Average returns are in percent per month and are denominated in domestic currency.

Table 3: Market returns and common risk factors for the European and Japanese market

Panel A: Europe

	FF			TR			
	Avg.	σ	t	Avg.	σ	t	ρ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VW	0.78	5.06	2.46	0.77	5.37	2.29	0.94
SMB	-0.07	2.34	-0.46	-0.10	2.29	-0.73	0.84
HML	0.43	2.40	2.86	0.40	2.20	2.92	0.84
WML	0.89	4.24	3.36	0.89	4.39	3.26	0.91

Panel B: Japan

	FF			TR			
	Avg.	σ	t	Avg.	σ	t	ρ
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VW	0.16	5.87	0.43	0.18	6.05	0.45	0.94
SMB	-0.05	3.32	-0.22	-0.14	3.02	-0.71	0.88
HML	0.50	2.93	2.69	0.63	3.08	3.19	0.81
WML	0.06	4.66	0.21	0.04	4.95	0.13	0.92

Note: This table reports descriptive statistics for the monthly value weighted (VW) market returns as well as the returns of the SMB, HML, and WML factors in %. We compare two different European (Panel A) and Japanese (Panel B) datasets with each other: the FF and TRD and TRW (TR) as described in Section 2.1. We report the average return (Avg.), the standard deviation of the returns (σ), the t-statistic (t), and the correlation coefficient between the returns of the two datasets (ρ). The t-statistic refers to the null hypothesis that the mean of the returns is zero. The time period ranges from 11/1990 to 02/2012. Average returns are in percent per month and are denominated in US$.

Table 4: Size returns – univariate sorts

	SMB		1-10		1-10		1-5	
	mean	t	mean	t	mean	t	mean	t
			NYSE BPs		Equal BPs		Equal BPs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Australia	0.09	0.48	0.95	2.24	3.51	6.23	2.29	4.67
Austria							0.24	0.62
Belgium							-0.18	-0.61
Canada	0.03	0.14	1.21	2.54	3.08	5.13	2.70	5.50
Denmark	-0.21	-0.87	-0.22	-0.66	0.38	0.89	0.18	0.57
Finland							0.08	0.13
France	-0.01	-0.03	0.31	1.00	1.3 0	3.13	0.68	1.89
Germany	-0.41	-2.04	-0.35	-1.27	0.81	1.66	0.17	0.54
Greece							1.79	2.51
Hong Kong	0.65	1.18	1.26	2.05	3.44	3.63	2.36	3.43
Ireland							1.36	1.82
Italy	-0.04	-0.19	-0.32	-1.07	-0.06	-0.15	0.12	0.35
Japan	-0.15	-0.81	0.18	0.58	0.64	1.83	0.49	1.60
Netherlands	-0.03	-0.17	0.13	0.46	0.51	1.04	0.12	0.36
Norway	0.15	0.61	-0.01	-0.03	0.87	1.72	0.67	1.65
Poland							0.85	1.05
Singapore	-0.30	-1.17	0.35	0.73	0.63	0.98	0.48	0.85
Spain							0.12	0.34
Sweden							0.05	0.10
Switzerland	0.01	0.03	0.10	0.40	0.06	0.17	0.08	0.28
Turkey							1.39	1.58
UK	0.02	0.08	0.03	0.11	0.65	1.72	0.18	0.52
US	0.22	1.02	-0.02	-0.06	1.45	2.36	0.45	0.86

Note: We report mean returns of the SMB factor for the countries in column (1), as well as the corresponding t-statistics (t) in column (2). Column (3) reports the mean raw return of a spread of a small decile and a large decile portfolio (using equal breakpoints), column (4) reports the corresponding t-values. We provide two versions of the 1-10 spread: one with equal breakpoints (columns (3) and (4) marked with "Equal BPs") and one with breakpoints based on the approximate NYSE breakpoints (columns (5) and (6) marked with "NYSE BPs"; see also Appendix A.2.2 and Table A.12). Column (7) reports the mean raw returns of a spread of a small quintile and a large quintile portfolio (using equal breakpoints), column (8) reports the corresponding t-values. We use the following time periods: 07/1991-02/2012: Australia, Austria, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Singapore, Spain, Sweden, Switzerland, UK, US; 07/2000-02/2012: Hong Kong; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway; 10/1995-02/2012: Poland; 07/2006-02/2012: Turkey.

Table 5: Risk-adjusted size returns – univariate sorts

	1-10				1-5			
	alpha	t	alpha	t	alpha	t	alpha	t
	NYSE BPs		Equal BPs		Equal BPs		Equal BPs	
	NYSE BP factors		NYSE BP factors		NYSE BP factors		Equal BP factors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Australia	0.20	0.53	2.68	4.32	1.56	2.86	1.35	2.81
Austria							0.23	0.86
Belgium							0.14	0.77
Canada	0.94	2.35	2.77	4.62	2.41	5.11	2.12	5.43
Denmark	0.31	1.00	0.57	1.61	0.37	1.78	0.36	2.42
Finland							0.04	0.17
France	0.27	1.52	1.44	4.04	0.76	2.23	0.66	2.23
Germany	0.07	0.50	1.20	2.48	0.52	2.05	0.40	1.88
Greece							1.15	3.72
Hong Kong	0.23	0.58	2.39	2.95	1.37	2.65	0.83	1.77
Ireland							1.26	2.14
Italy	-0.25	-1.36	0.01	0.04	0.17	0.71	0.16	0.82
Japan	0.07	0.73	0.55	2.60	0.42	2.41	0.33	2.36
Netherlands	0.24	1.10	0.61	1.65	0.25	1.01	0.26	1.22
Norway	-0.10	-0.41	1.09	2.70	0.58	1.98	0.49	1.85
Poland							-0.11	-0.22
Singapore	0.24	0.99	0.55	1.07	0.39	0.97	0.20	0.65
Spain							0.37	1.63
Sweden							0.37	0.95
Switzerland	0.08	0.53	0.16	0.56	0.22	1.34	0.18	1.17
Turkey							0.38	0.65
UK	-0.21	-1.75	0.33	1.48	-0.09	-0.48	-0.09	-0.56
US	-0.15	-0.65	1.46	2.43	0.43	0.91	0.21	0.52

Note: We report estimated regression slopes (or four-factor alphas) of the following regression:

$$\left(r_t^s - r_t^b\right) = \alpha + \beta_M * \left(r_{M,t} - r_{f,t}\right) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{WML} * WML_t + \varepsilon_t$$

Where r_t^s (r_t^b) is the return of the small (big) size decile or quintile in time t, $r_{M,t}$ is the return of the market portfolio in time t, $r_{f,t}$ is the riskfree rate proxy in time t, SMB_t, HML_t and WML_t are the factors as described in Appendix A.2.1, β_M, β_{SMB}, β_{HML}, and β_{WML} are the corresponding factor loadings, α is the four factor alpha, and ε_t is an error term. s=1 for all columns, b=10 for columns (1)-(4) and b=5 for columns (5)-(8). Column (1) reports the estimated four factor alpha of a spread of a small decile and a large decile portfolio (using NYSE breakpoints), column (2) reports the corresponding t-values of the four-factor regression. We provide two versions of the 1-10 spread: one with approximate NYSE breakpoints (columns (1) and (2) marked with "NYSE BPs") and one with equal breakpoints (columns (3) and (4) marked with "Equal BPs"; see also Appendix A.2.2 and Table A.12). Column (5) reports the estimated four factor alpha of a spread of a small quintile and a large quintile portfolio (using equal breakpoints) and column (6) reports the corresponding t-values of the four-factor regression. Columns (5) and (6) (labelled "NYSE BP factors") employ SMB, HML, and WML factors by applying approximate NYSE breakpoints. Columns (7) and (8) (labelled "Equal BP factors") employ SMB, HML, and WML factors by applying equal breakpoints. We report heteroscedasticity and autocorrelation robust t-statistics according to Newey and West (1987) with three lags for the correction of autocorrelation. We use the following time periods: 07/1991-02/2012: Australia, Austria, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Singapore, Spain, Sweden, Switzerland, UK, US; 07/2000-02/2012: Hong Kong; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway; 10/1995-02/2012: Poland; 07/2006-02/2012: Turkey.

Table 6: Momentum returns (relative to size) – bivariate sorts

	W-L small		W-L med		W-L big		W-L med – W-L big	
	mean	t	mean	t	mean	t	mean	t
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Australia	0.11	0.29	1.80	5.96	1.34	3.63	0.46	1.36
Canada	-1.49	-3.77	0.98	2.99	1.80	3.14	-0.82	-1.73
Denmark	1.19	3.51	1.15	3.63	1.28	3.12	0.07	0.16
France	1.20	4.08	1.25	3.97	0.50	1.45	0.74	2.47
Germany	0.84	2.51	1.79	5.46	0.71	1.77	0.99	2.69
Hong Kong	1.01	1.45	1.23	2.28	0.51	0.79	0.72	1.17
Italy	1.25	2.70	0.90	2.97	0.35	0.91	0.55	1.47
Japan	-0.02	-0.09	-0.01	-0.05	0.09	0.25	-0.11	-0.38
Netherlands	2.16	5.88	1.16	2.95	0.35	0.75	0.81	1.77
Norway	0.70	1.32	0.98	2.17	1.16	2.43	-0.18	-0.36
Singapore	-0.19	-0.40	0.55	1.34	-0.05	-0.10	0.60	1.50
Switzerland	1.11	4.08	1.15	3.79	0.43	1.13	0.73	2.23
UK	1.46	5.17	1.67	5.62	0.92	2.05	0.75	2.12
US	0.68	2.24	1.19	3.12	0.68	1.54	0.52	2.06

Note: We report average raw returns of three momentum spreads long in winners and short in losers (shorthand W-L) of a double sort on size and momentum for small (W-L small), medium (W-L med), big (W-L big) stocks, and the difference of the medium and big momentum spread (W-L med – W-L big), as well as the corresponding t-statistics. Momentum is calculated using the 12 previous months, skipping the most recent one. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Singapore, Switzerland, UK, US; 07/2000-02/2012: Hong Kong; 03/1993-02/2012: Japan; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table 7: Risk-adjusted momentum returns (relative to size) – bivariate sorts

	W-L small		W-L med		W-L big		W-L med – W-L big	
	alpha	t	alpha	t	alpha	t	alpha	t
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Australia	-0.44	-1.04	0.71	3.07	-0.37	-2.32	1.08	3.18
Canada	-2.02	-4.49	-0.06	-0.25	-0.61	-3.91	0.55	1.58
Denmark	0.87	2.34	0.48	1.93	-0.24	-1.39	0.72	2.25
France	0.86	3.15	0.68	3.51	-0.22	-1.64	0.90	3.16
Germany	0.23	0.83	1.02	4.89	-0.23	-0.79	1.25	3.33
Hong Kong	0.73	1.22	0.80	2.07	-0.31	-1.18	1.11	2.03
Italy	1.02	2.50	0.68	3.11	-0.12	-0.84	0.80	2.69
Japan	-0.13	-0.69	-0.09	-0.55	0.08	0.66	-0.17	-0.61
Netherlands	1.96	5.66	0.73	2.26	-0.39	-1.59	1.12	2.45
Norway	0.27	0.63	0.11	0.28	-0.2	-0.84	0.31	0.57
Singapore	-0.47	-1.45	0.31	1.12	-0.37	-2.13	0.68	1.67
Switzerland	0.99	4.29	0.64	3.02	-0.51	-3.12	1.15	3.62
UK	1.00	3.73	0.98	4.94	-0.41	-1.74	1.39	3.56
US	0.25	0.78	0.65	4.24	0.01	0.07	0.64	2.66

Note: We report estimated regression slopes (or four-factor alphas) of the following regression:

$$\left(r_t^{w,g} - r_t^{l,g}\right) = \alpha + \beta_M * \left(r_{M,t} - r_{f,t}\right) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{WML} * WML_t + \varepsilon_t$$

Where $r_t^{w,g}$ ($r_t^{l,g}$) is the return of the winner (loser) tercile of size group g in time t, $r_{M,t}$ is the return of the market portfolio in time t, $r_{f,t}$ is the riskfree rate proxy in time t, SMB_t, HML_t, and WML_t are the factors as described in Appendix A.2.1, β_M, β_{SMB}, β_{HML} and β_{WML} are the corresponding factor loadings, α is the four factor alpha, and ε_t is an error term. g=small for columns (1) and (2), g=medium (med) for columns (3) and (4), and g=big for columns (5) and (6).

We report the estimated four-factor alphas of three momentum spreads long in winners and short in losers (shorthand W-L) of a double sort on size and momentum for small (W-L small), medium (W-L med), big (W-L big) stocks, and the difference of the medium and big momentum spread (W-L med – W-L big) as well as the corresponding t-statistics. We report heteroscedasticity and autocorrelation robust t-statistics according to Newey and West (1987) with three lags for the correction of autocorrelation. Momentum is calculated using the 12 previous months, skipping the most recent one. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Singapore, Switzerland, UK, US; 07/2000-02/2012: Hong Kong; 03/1993-02/2012: Japan; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table 8: Returns of nine portfolios sorted on size and momentum

	small			med			big		
	losers	med	winners	losers	med	winners	losers	med	winners
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Australia	2.28	2.43	2.39	-0.66	0.22	1.14	-0.63	0.19	0.71
	(4.41)	(5.03)	(4.46)	(-1.53)	(0.69)	(2.70)	(-1.41)	(0.67)	(2.27)
Canada	4.94	3.78	3.45	0.33	0.77	1.30	-0.61	0.34	1.19
	(7.67)	(6.93)	(5.94)	(0.61)	(1.88)	(2.54)	(-1.03)	(1.02)	(2.99)
Denmark	-0.02	0.37	1.17	-0.51	0.19	0.84	-0.25	0.37	1.03
	(-0.06)	(1.49)	(3.66)	(-1.24)	(0.68)	(2.54)	(-0.53)	(0.97)	(3.16)
France	0.49	0.61	1.69	0.01	0.36	1.26	0.10	0.58	0.61
	(1.37)	(2.75)	(5.98)	(0.03)	(1.48)	(4.26)	(0.22)	(1.82)	(1.87)
Germany	-0.20	0.16	0.64	-1.08	-0.07	0.71	-0.11	0.27	0.70
	(-0.53)	(0.67)	(2.60)	(-2.64)	(-0.33)	(3.21)	(-0.21)	(0.76)	(2.17)
Hong Kong	2.89	2.75	3.89	0.26	0.78	1.49	0.08	0.11	0.59
	(3.18)	(3.67)	(4.25)	(0.30)	(1.12)	(2.15)	(0.10)	(1.82)	(1.05)
Italy	-0.33	0.08	0.92	-0.38	0.07	0.53	0.04	0.17	0.39
	(-0.67)	(0.22)	(1.99)	(-0.75)	(0.18)	(1.32)	(0.07)	(0.41)	(0.89)
Japan	0.44	0.38	0.41	0.05	0.06	0.03	-0.13	-0.30	-0.04
	(1.01)	(1.09)	(1.11)	(0.10)	(0.17)	(0.09)	(-0.27)	(-0.81)	(-0.11)
Netherlands	-0.56	0.65	1.60	0.09	0.85	1.25	0.35	0.54	0.70
	(-1.39)	(2.08)	(4.09)	(0.20)	(2.44)	(3.22)	(0.65)	(1.49)	(1.85)
Norway	0.75	0.75	1.45	0.36	1.07	1.34	-0.18	0.75	0.98
	(1.38)	(1.93)	(3.22)	(0.61)	(2.85)	(2.82)	(-0.29)	(1.67)	(1.96)
Singapore	1.50	1.26	1.32	0.32	0.74	0.87	0.73	0.83	0.68
	(2.05)	(1.97)	(2.21)	(0.45)	(1.29)	(1.63)	(1.13)	(1.61)	(1.61)
Switzerland	0.26	0.63	1.37	0.06	0.62	1.21	0.34	0.61	0.77
	(0.80)	(2.68)	(5.27)	(0.14)	(2.33)	(3.95)	(0.77)	(1.98)	(2.36)
UK	0.12	0.40	1.58	-0.50	0.07	1.17	-0.22	0.36	0.71
	(0.30)	(1.48)	(5.07)	(-1.11)	(0.23)	(3.59)	(-0.41)	(1.15)	(2.43)

US	1.71	1.63	2.39	-0.02	0.66	1.18	0.12	0.45	0.79
	(3.12)	(5.16)	(5.84)	(-0.03)	(2.10)	(3.12)	(0.21)	(1.43)	(2.69)

Note: We report average raw returns of nine portfolios sorted on size and momentum. Columns (1)-(3) shows the one third smallest stocks, columns (4)-(6) shows the middle third of stocks based on size and columns (4)-(6) shows the one third of biggest stocks. Within these three groups each first column shows the one third of stocks with the lowest momentum (losers), the second column shows the middle third of stocks based on momentum and the last column shows the one third with the highest momentum (winners). Momentum is calculated using the 12 previous months, skipping the most recent one. The numbers in parentheses represent t-statistics. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Singapore, Switzerland, UK, US; 07/2000-02/2012: Hong Kong; 03/1993-02/2012: Japan; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table 9: Risk-adjusted returns of nine portfolios sorted on size and momentum

	small			med			big		
	losers	med	winners	losers	med	winners	losers	med	winners
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Australia	1.75	1.55	1.31	-0.82	-0.38	-0.11	0.05	0.00	-0.32
	(4.06)	(4.00)	(2.86)	(-3.55)	(-2.06)	(-0.36)	(0.24)	(0.52)	(-0.97)
Canada	4.46	3.03	2.44	0.14	0.10	0.07	0.43	0.37	-0.17
	(7.41)	(6.66)	(4.90)	(0.44)	(0.47)	(0.27)	(2.28)	(1.74)	(-1.34)
Denmark	-0.06	0.19	0.81	-0.34	-0.03	0.14	0.32	0.05	0.08
	(-0.21)	(0.97)	(2.98)	(-1.60)	(-0.22)	(0.95)	(2.19)	(0.21)	(0.76)
France	0.31	0.23	1.17	-0.10	-0.11	0.58	0.12	0.12	-0.10
	(1.22)	(1.56)	(5.76)	(-0.55)	(-1.08)	(4.17)	(1.13)	(0.78)	(-1.14)
Germany	0.26	0.05	0.49	-0.57	-0.14	0.45	0.20	0.03	-0.02
	(1.31)	(0.29)	(2.28)	(-3.66)	(-1.05)	(3.40)	(0.88)	(0.23)	(-0.16)
Hong Kong	1.47	1.39	2.20	-0.84	-0.48	-0.04	-0.13	0.56	-0.44
	(2.97)	(2.97)	(3.62)	(-1.97)	(-1.30)	(-0.11)	(-0.42)	(2.00)	(-2.03)
Italy	-0.31	-0.05	0.71	-0.42	-0.08	0.26	0.10	0.06	-0.02
	(-1.20)	(-0.26)	(2.02)	(-2.63)	(-0.56)	(1.45)	(0.80)	(0.38)	(-0.18)
Japan	0.55	0.38	0.42	0.12	0.03	0.04	-0.03	-0.25	0.05
	(3.54)	(3.10)	(2.29)	(1.13)	(0.34)	(0.26)	(-0.29)	(-2.31)	(0.58)
Netherlands	-0.83	0.32	1.12	-0.14	0.41	0.59	0.22	0.08	-0.17
	(-3.13)	(1.24)	(3.47)	(-0.48)	(2.29)	(2.36)	(1.21)	(0.48)	(-1.12)
Norway	0.32	0.05	0.59	-0.04	0.35	0.07	-0.03	0.09	-0.23
	(1.02)	(0.21)	(1.76)	(-0.12)	(1.50)	(0.31)	(-0.14)	(0.56)	(-1.40)
Singapore	1.02	0.58	0.56	-0.17	0.04	0.14	0.30	0.13	-0.07
	(2.82)	(2.00)	(1.87)	(-0.91)	(0.30)	(0.76)	(1.56)	(0.55)	(-0.57)
Switzerland	-0.22	0.23	0.76	-0.39	0.05	0.25	0.22	0.02	-0.29
	(-1.07)	(1.26)	(4.45)	(-1.97)	(0.32)	(1.53)	(1.51)	(0.10)	(-2.58)
UK	-0.01	-0.03	0.99	-0.54	-0.30	0.44	0.24	0.06	-0.17
	(-0.40)	(-0.18)	(4.80)	(-3.43)	(-2.22)	(3.61)	(1.10)	(0.55)	(-1.72)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
US	1.65	1.34	1.90	-0.35	0.04	0.30	-0.02	0.01	-0.01
	(3.47)	(4.82)	(5.84)	(-1.79)	(0.34)	(1.63)	(-0.17)	(0.18)	(-0.19)

Note: We report estimated regression slopes (or four-factor alphas) of the following regression:

$$\left(r_t^{g,m} - r_{f,t}\right) = \alpha + \beta_M * \left(r_{M,t} - r_{f,t}\right) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{WML} * WML_t + \varepsilon_t$$

Where $r_t^{g,m}$ is the return of a portfolio where the stock are both contained in the size tercile g and the momentum tercile m in time t, $r_{M,t}$ is the return of the market portfolio in time t, $r_{f,t}$ is the riskfree rate proxy in time t, SMB_t, HML_t, and WML_t are the factors as described in Appendix A.2.1, β_M, β_{SMB}, β_{HML} and β_{WML} are the corresponding factor loadings, α is the four factor alpha, and ε_t is an error term. g=small (columns (1)-(3)), g=medium (med) (columns (4)-(6), and g=big (columns (7)-(9)). m=losers (columns (1), (4) and (7)), m=medium (med) (columns (2), (5) and (8)), and m=winners (columns (3),(6) and (9)).

We report the estimated four-factor alphas of nine portfolios sorted on size and momentum. Columns (1)-(3) shows the one third smallest stocks, columns (4)-(6) shows the middle third of stocks based on size, and columns (4)-(6) shows the one third of biggest stocks. Within these three groups each first column shows the one third of stocks with the lowest momentum (losers), the second column shows the middle third of stocks based on momentum, and the last column shows the one third with the highest momentum (winners). Momentum is calculated using the 12 previous months, skipping the most recent one. The numbers in parentheses represent t-statistics of the four-factor alphas. We report heteroscedasticity and autocorrelation robust t-statistics according to Newey and West (1987) with three lags for the correction of autocorrelation. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Singapore, Switzerland, UK, US; 07/2000-02/2012: Hong Kong; 03/1993-02/2012: Japan; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table 10: Size returns (relative to momentum) – bivariate sorts

	S-B losers		S-B med		S-B winners	
	mean	t	mean	t	mean	t
	(1)	(2)	(3)	(4)	(5)	(6)
Australia	2.91	6.07	2.24	4.93	1.68	3.66
Canada	5.55	8.35	3.44	6.96	2.26	4.31
Denmark	0.23	0.57	0.00	-0.01	0.14	0.41
France	0.39	1.04	0.03	0.11	1.08	3.41
Germany	-0.10	-0.27	-0.11	-0.37	-0.05	-0.17
Hong Kong	2.81	3.64	1.69	2.42	3.30	4.57
Italy	-0.36	-1.02	-0.90	-0.29	0.53	1.17
Japan	0.57	1.78	0.68	2.57	0.45	1.50
Netherlands	-0.91	-2.14	0.11	0.32	0.90	2.40
Norway	0.94	1.85	0.00	-0.01	0.47	0.96
Singapore	0.78	1.48	0.43	0.88	0.64	1.45
Switzerland	-0.08	-0.23	0.02	0.07	0.60	2.03
UK	0.34	0.76	0.04	0.12	0.88	2.91
US	1.60	3.02	1.17	3.52	1.60	4.42

Note: We report average raw returns of three size spreads long in small stocks and short in big stocks (shorthand S-B) of a double sort on size and momentum for loser (S-B losers), medium (S-B med), and winner (S-B winners) stocks, as well as the corresponding t-statistics. Momentum is calculated using the 12 previous months, skipping the most recent one. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Switzerland, UK, US; 07/2000-02/2012: Hong Kong; 03/1993-02/2012: Japan; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway, Singapore.

Table 11: Risk-adjusted size returns (relative to momentum) – bivariate sorts

	S-B losers		S-B med		S-B winners	
	alpha	t	alpha	t	alpha	t
	(1)	(2)	(3)	(4)	(5)	(6)
Australia	1.70	3.76	1.55	3.65	1.63	3.31
Canada	4.02	6.56	2.65	5.34	2.61	5.09
Denmark	-0.38	-1.11	0.15	0.54	0.73	2.52
France	0.19	0.61	0.11	0.50	1.27	5.86
Germany	0.05	0.15	0.02	0.10	0.51	1.98
Hong Kong	1.60	2.72	0.83	1.28	2.64	4.26
Italy	-0.41	-1.45	-0.11	-0.47	0.73	1.96
Japan	0.58	2.66	0.63	4.31	0.37	1.63
Netherlands	-1.05	-3.24	0.23	0.75	1.29	3.54
Norway	0.35	0.80	-0.04	-0.16	0.81	2.28
Singapore	0.83	1.72	0.65	1.45	0.69	1.93
Switzerland	-0.44	-1.63	0.21	0.90	1.05	5.18
UK	-0.35	-0.60	-0.09	-0.44	1.16	4.95
US	1.67	3.29	1.32	4.42	1.91	5.83

Note: We report estimated regression slopes (or four-factor alphas) of the following regression:

$$\left(r_t^{s,m} - r_t^{b,m}\right) = \alpha + \beta_M * \left(r_{M,t} - r_{f,t}\right) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{WML} * WML_t + \varepsilon_t$$

Where $r_t^{s,m}$ ($r_t^{b,m}$) is the return of the small (big) size tercile of momentum group m in time t, $r_{M,t}$ is the return of the market portfolio in time t, $r_{f,t}$ is the riskfree rate proxy in time t, SMB_t, HML_t, and WML_t are the factors as described in Appendix A.2.1, β_M, β_{SMB}, β_{HML}, and β_{WML} are the corresponding factor loadings, α is the four factor alpha, and ε_t is an error term. m=losers for columns (1) and (2), m=medium (med) for columns (3) and (4), and m=winners for columns (5) and (6).

We report the estimated four-factor alphas of three size spreads long in small stocks and short in big stocks (shorthand S-B) of a double sort on size and momentum for loser (S-B losers), medium (S-B med), and winner (S-B winners) stocks, as well as the corresponding t-statistics. We report heteroscedasticity and autocorrelation robust t-statistics according to Newey and West (1987) with three lags for the correction of autocorrelation. Momentum is calculated using the 12 previous months, skipping the most recent one. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Singapore, Switzerland, UK, US; 07/2000-02/2012: Hong Kong; 03/1993-02/2012: Japan; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table 12: Critical trading costs of size returns – univariate sorts

	SMB		1-10		1-10		1-5	
	10%	5%	10%	5%	10%	5%	10%	5%
			NYSE BPs		Equal BPs		Equal BPs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Australia	neg	neg	397.57	218.41	2197.74	2047.16	1502.63	1346.62
Austria							neg	neg
Belgium							neg	neg
Canada	neg	neg	525.27	340.49	1555.40	1415.14	1764.07	1619.99
Denmark	neg	neg	neg	neg	neg	neg	neg	neg
Finland							neg	neg
France	neg	neg	neg	neg	784.24	617.81	136.60	neg
Germany	neg	neg	neg	neg	1.79	neg	neg	neg
Greece							842.92	538.02
Hong Kong	neg	neg	113.51	neg	1649.87	1400.56	1136.31	920.80
Ireland							155.32	neg
Italy	neg	neg	neg	neg	neg	neg	neg	neg
Japan	neg	neg	neg	neg	91.40	neg	neg	neg
Netherlands	neg	neg	neg	neg	neg	neg	neg	neg
Norway	neg	neg	neg	neg	32.59	neg	2.02	neg
Poland							neg	neg
Singapore	neg	neg	neg	neg	neg	neg	neg	neg
Spain							neg	neg
Sweden							neg	neg
Switzerland	neg	neg	neg	neg	neg	neg	neg	neg
Turkey							neg	neg
UK	neg	neg	neg	neg	26.73	neg	neg	neg
US	neg	neg	neg	neg	93.35	neg	neg	neg

Note: We calculate critical trading costs as follows:

$$tc_{crit} = \frac{\frac{1}{T}\sum_{t=1}^{T} sp_t - t_{crit}\sqrt{\frac{1}{T}\sum_{t=1}^{T}(sp_t - \mu)^2}}{\frac{1}{T}\sum_{t=1}^{T} to_t}$$

With T as the number of periods, t_{crit} is the critical value of the assumed t-test, sp_t as the return of the spread portfolio with mean μ, and to_t as the portfolio turnover. Note in the spread portfolio, long small stocks and short in big stocks, we already substract the average trading costs of 15 basis points for the big stocks. We report the critical trading costs for the SMB factor (columns (1) and (2)), the 1-10 spread with NYSE breakpoints (columns (3) and (4)), the 1-10 spread with equal breakpoints (columns (5) and (6)), and the 1-5 spread with equal breakpoints (columns (7) and (8)). The critical trading costs are denoted in basis points. We report critical trading costs for two significance levels: 10% (columns (1), (3), (5) and (7)) and 5% (columns (2), (4), (6) and (8)). Since we report only positve crtical trading costs we denote negative values simply with 'neg'. We use the following time periods: 07/1991-02/2012: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Singapore, Spain, Sweden, Switzerland, UK, US; 07/2001-02/2012: Hong Kong; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway; 01/1996-02/2012: Poland; 07/2006-02/2012: Turkey.

Table 13: Turnover and trading volume of the smallest and biggest of the ten size portfolios (July)

	Portfolio turnover				Trading volume			
	NYSE BPs		Equal BPs		NYSE BPs		Equal BPs	
	Pf 1	Pf 10	Pf 1	Pf 10	Pf 1	Pf 10	Pf 1	Pf 10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Australia	72.78	12.3	121.08	10.99	185.21	30,120.02	13.58	36,336.35
Canada	75.69	12.03	122.96	9.75	259.96	33,031.54	4.71	43,871.07
Denmark	40.3	15.04	60.85	12.72	38.27	2,936.33	1.62	4,233.34
France	48.25	16.44	82.59	10.05	132.76	60,242.40	2.64	78,394.56
Germany	68.76	13.8	456.68	11.75				
Hong Kong	73.21	14.97	100.85	13.17	328.07	8,886.01	33.4	27,266.42
Italy	56.96	19.54	196.30	16.26	405.61	45,546.36	33.87	56,034.66
Japan	41.04	12.07	68.38	9.96	3,769.94	114,354.60	206.02	160,110.17
Netherlands	40.54	14.56	87.93	8.99	251.27	23,325.42	27.27	34,443.28
Norway	63.51	17.73	110.36	18.10	117.72	7,008.63	5.54	9,711.88
Singapore	59.8	21.53	93.71	17.98	324.57	4,078.23	33.2	6,759.47
Switzerland	43.67	11.07	74.00	8.42	198.21	28,621.76	9.15	35,413.20
UK	69.14	10.34	103.58	8.47	316.98	115,511.91	9.19	146,697.04
US	74.19	11.49	153.94	9.39	3,814.54	1,088,994.16	375.85	1,406,860.74
Average	59.13	14.49	130.94	11.86	780.24	120,204.41	58.16	157,394.78

Note: We report the average turnover and average trading volume of the smallest (Pf 1) and biggest portfolios (Pf 10) involved in the size strategies examined. We calculate turnover based on a value weighted scheme, according to the corresponding portfolios. We calculate trading volume by multiplying the TRD variable 'turnover by volume' (VO) with the 'adjusted price' (P) on a monthly basis. Turnover as well as trading volume is reported for the July values of the dataset. Turnover is reported in per cent and on a monthly basis. Trading volume is reported in million US$ on a monthly basis. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Japan, Singapore, Switzerland, UK, US; 07/2001-02/2012: Hong Kong; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table 14: Turnover and trading volume of the smallest and biggest of the five size portfolios (July)

	Portfolio turnover		Trading volume	
	Pf 1	Pf 5	Pf 1	Pf 5
	(1)	(2)	(3)	(4)
Australia	101.52	9.79	24.28	39,603.31
Austria	63.29	18.38	4.79	2,446.18
Belgium	53.31	8.62	3.26	6,016.05
Canada	100.85	8.61	15.27	46,479.92
Denmark	57.29	9.49	7.73	4,897.47
Finland	57.65	12.43	4.56	10,672.19
France	67.45	8.91	13.29	81,851.91
Germany	165.93	10.38		
Greece	77.61	17.51	70.47	2,800.15
Hong Kong	93.85	12.89	123.5	30,140.51
Ireland	75.48	10.74	3.04	2,069.88
Italy	102.42	13	88.9	60,747.06
Japan	56.46	8.72	835.84	182,034.72
Netherlands	68.59	7.38	43.87	39,315.98
Norway	89.8	15.86	23.14	10,809.34
Poland	77.63	36.98	37.9	1,915.29
Singapore	78.59	15.24	101.83	7,146.36
Spain	67.97	10.88	66.8	36,863.32
Sweden	85.73	11.42	14.76	20,203.65
Switzerland	55.72	7.76	28.9	38,057.23
Turkey	71.85	23.25	477.64	14,595.30
UK	118.32	7.84	40.11	157,643.20
US	116.33	8.31	805.15	1,578,656.99
Average	82.77	12.80	128.87	107,953.00

Note: We report the average turnover and average trading volume of the smallest (Pf 1) and biggest portfolios (Pf 5) involved in the size strategies examined. We calculate turnover based on a value weighted scheme, according to the corresponding portfolios. We calculate trading volume by multiplying the TRD variable 'turnover by volume' (VO) with the 'adjusted price' (P) on a monthly basis. Turnover as well as trading volume is reported for the July values of the dataset. Turnover is reported in per cent and on a monthly basis. Trading volume is reported in million US$ on a monthly basis. We use the following time periods: 07/1991-02/2012: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Singapore, Spain, Sweden, Switzerland, UK, US; 01/2001-02/2012: Hong Kong; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway; 01/1996-02/2012: Poland; 07/2006-02/2012: Turkey.

Table 15: Momentum returns (relative to size), trading cost-adjusted– bivariate sorts

	W-L small		W-L med		W-L big		W-L med – W-L big	
	mean	t	mean	t	mean	t	mean	t
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Australia	-0.35	-0.92	1.48	4.90	1.04	2.81	0.44	1.33
Canada	-2.01	-5.09	0.63	1.93	1.53	2.67	-0.90	-1.90
Denmark	0.85	2.51	1.04	2.80	1.04	2.54	0.00	-0.01
France	0.84	2.85	0.94	2.98	0.23	0.66	0.70	2.35
Germany	0.48	1.43	1.49	4.55	0.54	1.20	0.95	2.58
Hong Kong	0.77	1.04	0.92	1.60	0.38	0.57	0.54	0.90
Italy	0.90	1.94	0.58	1.92	0.06	0.17	0.52	1.39
Japan	-0.43	-1.75	-0.36	-1.39	-0.16	-0.44	-0.20	-0.72
Netherlands	1.83	5.01	0.86	2.18	0.04	0.08	0.82	1.79
Norway	0.31	0.58	0.62	1.37	0.79	1.65	-0.17	-0.34
Singapore	-0.61	-1.32	0.20	0.49	-0.44	-0.87	0.64	1.61
Switzerland	0.77	2.83	0.87	2.85	0.11	0.29	0.76	2.32
UK	1.11	3.93	1.38	4.63	0.63	1.40	0.75	2.11
US	0.23	0.75	0.87	2.28	0.41	0.94	0.46	1.84

Note: We report average raw returns of three momentum spreads long in winners and short in losers (shorthand W-L) of a double sort on size and momentum for small (W-L small), medium (W-L med), big (W-L big) stocks, and the difference of the medium and big momentum spread (W-L med – W-L big), as well as the corresponding t-statistics. Momentum is calculated using the 12 previous months, skipping the most recent one. We assume that trading costs for small stocks are 30 basis points before 2001 and 40 basis points from 2001 on. For big stocks we assume trading costs of 15 basis points over the whole time period. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Singapore, Switzerland, UK, US; 07/2001-02/2012: Hong Kong; 03/1993-02/2012: Japan; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table 16: Risk-adjusted momentum returns (relative to size), trading cost-adjusted– bivariate sorts

	W-L small		W-L med		W-L big		W-L med – W-L big	
	alpha	t	alpha	t	alpha	t	alpha	t
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Australia	-0.80	-1.94	0.60	2.66	-0.36	-2.35	0.95	2.95
Canada	-2.46	-5.52	-0.25	-1.02	-0.51	-3.28	0.26	0.75
Denmark	0.60	1.68	0.37	1.53	-0.17	-0.98	0.54	1.71
France	0.65	2.48	0.60	3.19	-0.19	-1.47	0.79	2.90
Germany	0.00	-0.01	0.90	4.34	-0.19	-0.75	1.09	3.06
Hong Kong	0.36	0.62	0.55	1.48	-0.23	-0.83	0.78	1.46
Italy	0.85	2.10	0.55	2.51	-0.04	-0.29	0.60	2.00
Japan	-0.36	-1.85	-0.23	-1.39	0.17	1.42	-0.39	-1.45
Netherlands	1.75	5.08	0.66	2.04	-0.30	-1.27	0.97	2.12
Norway	0.11	0.26	0.06	0.15	-0.14	-0.61	0.19	0.38
Singapore	-0.59	-1.94	0.30	1.07	-0.23	-1.35	0.53	1.31
Switzerland	0.77	3.40	0.60	2.76	-0.44	-2.81	1.04	3.30
UK	0.79	3.07	0.88	4.58	-0.34	-1.47	1.22	3.20
US	-0.07	-0.22	0.58	3.84	0.04	0.33	0.53	2.26

Note: We report estimated regression slopes (or four-factor alphas) of the following regression:

$$\left(r_t^{w,g} - r_t^{l,g}\right) = \alpha + \beta_M * \left(r_{M,t} - r_{f,t}\right) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{WML} * WML_t + \varepsilon_t$$

Where $r_t^{w,g}$ ($r_t^{l,g}$) is the return of the winner (loser) tercile of size group g in time t, $r_{M,t}$ is the return of the market portfolio in time t, $r_{f,t}$ is the riskfree rate proxy in time t, SMB_t, HML_t, and WML_t are the factors as described in Appendix A.2.1, β_M, β_{SMB}, β_{HML}, and β_{WML} are the corresponding factor loadings, α is the four factor alpha, and ε_t is an error term. g=small for columns (1) and (2), g=medium (med) for columns (3) and (4), and g=big for columns (5) and (6).

We report the estimated four-factor alphas of three momentum spreads long in winners and short in losers (shorthand W-L) of a double sort on size and momentum for small (W-L small), medium (W-L med), big (W-L big) stocks, and the difference of the medium and big momentum spread (W-L med – W-L big), as well as the corresponding t-statistics. We report heteroscedasticity and autocorrelation robust t-statistics according to Newey and West (1987) with three lags for the correction of autocorrelation. Momentum is calculated using the 12 previous months, skipping the most recent one. We assume that trading costs for small stocks are 30 basis points before 2001 and 40 basis points from 2001 on. For big stocks we assume trading costs of 15 basis points over the whole time period. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Singapore, Switzerland, UK, US; 07/2001-02/2012: Hong Kong; 03/1993-02/2012: Japan; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table 17: Critical trading costs of momentum returns (relative to size) – bivariate sorts

	W-L small		W-L med		W-L big	
	10%	5%	10%	5%	10%	5%
	(1)	(2)	(3)	(4)	(5)	(6)
Australia	neg	neg	131.97	122.36	65.96	55.54
Canada	neg	neg	40.51	31.09	85.02	67.20
Denmark	65.41	54.39	79.95	67.31	68.59	54.02
France	68.46	59.65	77.29	66.83	neg	neg
Germany	28.09	17.94	138.10	126.73	6.00	neg
Hong Kong	5.47	neg	34.47	17.83	neg	neg
Italy	46.78	32.88	41.22	31.49	neg	neg
Japan	neg	neg	neg	neg	neg	neg
Netherlands	168.66	156.16	55.65	42.29	neg	neg
Norway	neg	neg	21.51	8.65	29.75	17.94
Singapore	neg	neg	neg	neg	neg	neg
Switzerland	68.33	59.53	76.30	65.12	neg	neg
UK	98.99	90.18	131.12	120.75	17.01	3.96
US	13.75	6.56	57.01	44.86	neg	neg

Note: We calculate critical trading costs as follows:

$$tc_{crit} = \frac{\frac{1}{T}\sum_{t=1}^{T} sp_t - t_{crit}\sqrt{\frac{1}{T}\sum_{t=1}^{T}(sp_t-\mu)^2}}{\frac{1}{T}\sum_{t=1}^{T} to_t}$$

With T as the number of periods, t_{crit} is the critical value of the assumed t-test, sp_t as the return of the spread portfolio with mean μ, and to_t as the portfolio turnover. We report the critical trading costs for three momentum spreads long in winners and short in losers (shorthand W-L) of a double sort on size and momentum for small (W-L small), medium (W-L med), and big (W-L big) stocks. The critical trading costs are denoted in basis points. We report critical trading costs for two significance levels: 10% (columns (1), (3) and (5)) and 5% (columns (2), (4) and (6)). Since we report only positve crtical trading costs we denote negative values simply with 'neg'. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Japan, Singapore, Switzerland, UK, US; 07/2001-02/2012: Hong Kong; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table 18: Turnover of nine portfolios sorted on size and momentum

	small			med			big		
	losers	med	winners	losers	med	winners	losers	med	winners
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Australia	55.90	102.74	75.99	51.98	76.58	46.91	70.26	39.76	41.38
Canada	69.40	114.25	83.96	55.56	84.74	53.38	64.70	37.89	36.23
Denmark	41.91	66.22	55.05	46.37	65.76	45.99	56.73	73.32	31.89
France	44.19	85.68	60.33	48.74	68.96	45.83	59.52	59.98	43.08
Germany	45.86	77.82	58.41	46.89	69.89	43.88	61.34	55.55	36.09
Hong Kong	54.21	85.64	76.63	55.82	78.00	52.69	60.34	42.29	41.54
Italy	46.98	79.30	57.75	51.75	76.59	46.41	68.52	61.19	37.78
Japan	52.42	84.12	66.62	52.78	80.20	52.34	58.34	75.16	39.74
Netherlands	42.24	79.48	49.93	47.13	68.14	45.41	60.65	69.22	51.78
Norway	46.95	85.84	62.28	56.75	79.87	53.89	79.17	67.43	48.19
Singapore	50.73	88.71	70.56	53.51	77.31	52.21	91.69	76.01	45.54
Switzerland	41.87	76.58	55.10	44.47	72.77	41.13	66.68	74.54	46.43
UK	44.32	79.30	56.55	47.37	69.14	42.81	63.82	50.25	44.49
US	56.32	94.90	76.07	51.20	68.88	48.02	64.83	42.10	37.29

Note: We report the average turnover of nine portfolios sorted on size and momentum. We calculate turnover based on a value weighted scheme, according to the corresponding portfolios. Turnover is reported in per cent and on a monthly basis. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Japan, Singapore, Switzerland, UK, US; 07/2001-02/2012: Hong Kong; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table 19: Trading volume of nine portfolios sorted on size and momentum

	small			med			big		
	losers	med	winners	losers	med	winners	losers	med	winners
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Australia	28.41	15.19	22.93	138.48	94.49	210.44	3,670.25	21,213.37	13,175.97
Canada	22.93	13.76	20.71	126.36	107.96	207.64	4,459.54	22,237.62	20,834.19
Denmark	7.83	5.21	6.83	48.57	31.83	41.30	1,235.66	1,643.12	2,462.26
France	29.57	9.93	28.10	147.35	115.76	161.36	16,532.48	35,285.23	25,494.07
Hong Kong	114.49	52.75	78.33	334.32	286.25	549.56	6,011.45	14,624.70	12,548.78
Italy	128.36	76.96	109.40	337.16	288.11	433.86	11,788.77	25,278.27	20,156.41
Japan	472.86	269.74	487.42	2,313.88	1,836.80	3,664.68	48,082.50	54,841.40	85,428.32
Netherlands	33.11	29.25	33.51	380.93	289.26	343.76	10,699.57	17,071.01	15,712.39
Norway	31.14	15.38	24.51	156.52	102.25	180.18	1,856.13	4,370.07	5,281.77
Singapore	35.30	26.76	49.37	128.29	130.57	262.20	1,326.70	3,060.99	3,247.56
Switzerland	33.15	21.24	25.82	260.25	166.87	254.52	12,994.38	15,996.27	11,847.22
UK	94.10	29.74	39.35	508.56	356.41	579.70	24,078.50	75,610.70	58,974.01
US	734.59	228.59	526.67	7,697.13	4,677.37	11,571.33	193,840.94	682,671.23	787,836.47

Note: We report the average trading volume of the nine portfolios sorted on size and momentum. We calculate trading volume by multiplying the TRD variable turnover by volume (VO) with the adjusted price (P) on a monthly basis. Trading volume is reported in million US$ on a monthly basis. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, Japan, Singapore, Switzerland, UK, US; 01/1992-02/2012: France; 05/1994-02/2012: Italy; 07/2001-02/2012: Hong Kong; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

A. Supplementary Appendix

Please note: The following supplementary appendices are not meant for publication in print. They can be made available on a Journal website and the authors' websites upon publication.

A.1. Data preparation

Like Ince and Porter (2006, p. 465), we use TRD constituent lists to construct our dataset. Besides research lists, we also use dead lists, TRW lists and for certain countries specific lists provided by TRD and TRW. The TRW dataset is in principle available from 1980 onwards, but, as noted by the data provider, "statistically significant company and data item representation is best represented from January 1985 forward" (Thomson Financial, 2007, p. 4). Thus, we use data from 1985 onwards.[34] We use the "dead lists" of companies that cease to exist (due to mergers, bankruptcy or other reasons) to control for survivorship bias and TRW lists and sometimes additional lists to get a population as large as possible.[35] The lists are provided in Sections A.1.1 (US) and A.1.2 (International).

On the basis of this initial sample (53,517 unique US firms and 43,376 unique European firms)[36], we first sort out firms which are obviously not a member of our population of interest. To do this we use firm characteristics which are assumed to be constant over time, thus employing "static screens." Specifically, our first screening procedure is to keep major listings (MAJOR="Y"), stocks located in the domestic market (e.g. GEOGN="UNITED STATES", for the US and likewise for other countries) and firms of the equity type (TYPE="EQ"). There are different reasons why firms are excluded by the static screens: either the firms are not major listings (e.g. preferred shares), foreign stocks, additional listings (e.g. closed-end-funds, REITs, ADRs, etc.) or simply no data are available. See also Table A.1 for an overview of theses

[34] Ulbricht and Weiner (2005, p. 12-16, fig. 2-4) find a difference in the firm size structures between the Thomson Reuters Worldscope and COMPUSTAT databases which "diminishes over the years and is virtually not noticeable after 2002". Since Thomson Reuters Worldscope was "originally developed by fund managers", "more interesting and better visible firms, i.e. large firms, were added to the database first" (Ulbricht and Weiner, 2005, p. 3).

[35] Nonetheless, it is very likely that not all dead stocks are captured by the dead lists (Ince and Porter, 2006, p. 470, note that firms like Atlantic Richfield Co., GTE Corp. and Honeywell are not included in the dead stock lists), and not all remaining firms are captured by the other lists available on Thomson Reuters Datastream and Thomson Reuters Worldscope.

[36] Figures for the other samples are: 5,230 (Japan); 1,847 (Hong Kong); 1,095 (Singapore); 6,005 (Australia) and 13,790 (Canada).

static screens (SS01-SS03). We also use some additional static filters (SS04 and SS05). We include stocks listed on all domestic exchanges.

[Table A.1 here]

After these static screens, 32,585 firms remain for the US and 23,709 for Europe.[37] For these firms, we then extract time series data from the database. The time series draws are separated into yearly data (TRW) and monthly data (TRD). To break down the yearly information into a monthly frequency, we use the TRW 'fiscal year end' information (TRW item 05350).[38]

For the correction of the monthly data we apply dynamic screens suggested by Ince and Porter (2006) as well as additional filters. Table A.2 summarizes the employed dynamic screening procedures.[39]

[Table A.2 here]

Tables A.3 and A.4 (for the other countries see Tables A.5—A.9) list the number of firms for different stages of the data preparation process as well as the actual employed number of firms in case of the value weighted factors for the US and for Europe. From the 32,593 (23,709) firms that remain after the static screens, 29,150 (20,031) fulfil the minimum requirements of having at least one point in time with jointly a non-missing 'dscd code' (DSCD) and 'price' (P). Of these, 26,034 (17,429) US (European) firms pass the time series screens described in Table A.2. In the end we use 15,239 (11,315) US (European) firms to construct the value weighted market factor, 14,129 (11,239) firms to construct the SMB and HML factors

[37] Figures for the other samples are: 5,064 (Japan); 1,616 (Hong Kong); 989 (Singapore); 3,749 (Australia) and 9,328 (Canada).

[38] Occasionally, the fiscal year entry (such as "12/1999") is missing, but at least one item of the actual Thomson Reuters Worldscope company-specific data is known. In such cases, to avoid losing these datapoints, we fill in the fiscal year information if the fiscal year information of either the preceding (e.g. "12/1998") or succeeding year (e.g. "12/2000") in the data is contained in the data. If fiscal year ends from the year before and after the missing fiscal year end information are known, but from a different month, we use the latest month (e.g. if the preceding fiscal year end is "12/1998" and the succeding fiscal year end is "09/2000" then we use "12/1999" as the fiscal year end for 1999).

[39] In addition to the screens employed in this section, we exclude six US-stocks by hand. We do this because they have a hughe influence on the small decile portfolio (equal breakpoints) in the size sorts (other sorts and the factors are rather unaffected). Marked values and/or returns of these stocks are most likely erroneous. For other county samples we do not observe such influential potentially erroneous observations. The firms in question are (DSCD-codes in parantheses): EMTA Holdings (898428); Better Environment Concepts (872571); Spectral Capital (26972T); Crystal Properties Holdings (513370); Savenergy Holdings (878979) and RINO International (329456).

and 15,238 (11,310) firms to construct the WML factor. All numbers are for unique firms over the whole time span.

The US sample (with respect to the SMB and HML factors) starts with a little less than 2,000 firms in the early eighties, rises to a maximum of about 7,000 in the year 2000 and falls from then on steadily to about 5,000 firms in 2011. The European sample (with respect to the SMB and HML factors) starts with less than 1,000 firms in 1987,[40] rises to more than 5,000 firms in 1999 and then stays between 5,000 and 6,000 firms until the end of the sample period. The detailed listing of the evolution of the number of firms can also be seen in Tables A.3 and A.4.

[Tables A.3 — A.9 here]

Some further issues cannot be fixed by the suggestions of Ince and Porter (2006), but are important for the present application. Most important, the exchange affiliation is only recorded for the current point in time. We choose to use all stocks which are available on TRD and TRW, which means that there are not only NYSE-, AMEX- or NASDAQ-listed stocks in the US sample. We note that this implies that our US sample is drawn from a different population than the sample population described by Fama and French (1993). The alternative, using only firms listed on the NYSE, AMEX, or NASDAQ at the end of the sample period, would result in a sample suffering from survivorship bias. We do not exclude financials.

There are two additional issues for European stocks, which either are not relevant or of minor relevance for US stocks. First, the adoption of the Euro in January 2002 implies that there exist two currencies in all countries that switched to the Euro. Data of companies which are traded after January 2002 are all dominated in Euros, whereas data of companies which are delisted before January 2002 are denominated in the old currency of the respective country. This can easily be fixed. We use the fixed euro

[40] Since most exchange rate series available on Thomson Reuters Datastream start in 1987 (or later), we do not calculate joint European SMB, HML and WML factors before 1987, because we cannot calculate returns denominated in one currency and also cannot express market capitalizations for value weighting in one joint currency.

conversion rate and express all cash values (like size) in euro values.[41]

Second, for some European countries dividend data are obviously erroneous. We observe that for some companies dividends are of a magnitude of about ten times the actual price series, which means that screening procedures like DS06 or DS07 (see Table A.2) result in unusually high returns of several hundered percents whenever dividend payments are distributed. A casual inspectation shows that sometimes dividend payments made later are a fraction of the unusually high dividends, which leads us to the conjecture that a decimal or other error occurred. In order to correct this issue, we apply the following procedure (see Table A.2, screen DS05): Whenever a dividend payment is observed that is greater than 50% of the adjusted price, we divide the TRD dividend by a certain value.[42] We apply this screen also to the US dataset, although this issue is not of practical relevance there.

A.1.1. Constituent lists for the US sample

We collect data from the following list types: research lists (FUSAA, FUSAB, FUSAC, FUSAD, FUSAE, FUSAF, FUSAG)[43], dead lists (DEADUS1, DEADUS2, DEADUS3, DEADUS4, DEADUS5, DEADUS6) and TRW lists (WSUS1, WSUS2, WSUS3, WSUS4, WSUS5, WSUS6, WSUS7, WSUS8, WSUS9, WSUS10, WSUS11, WSUS12, WSUS13, WSUS14, WSUS15, WSUS16, WSUS17, WSUS18).[44,45]

---

[41] Note that this procedure leaves the returns unaffected. Since value weighted market returns are generated by weighting with lagged size, this transformation may have a noticeable effect on value weighted market returns (and other return series which use value weighting, such as the risk factors) if a significant number of companies exit the sample before the euro changeover. This effect will be stronger the closer the relation between average returns and size is.

[42] The problem of the unusually high dividends is especially severe for the following countries: Belgium, Greece, Italy, Luxembourg, Portugal, Slovakia, Spain and Turkey. It turns out that dividing by 10, 100 or 1000 works well. In the case of Greece, Iceland, Italy and Turkey whenever a dividend payment is observed that is greater than 50% of the adjusted price, we divide dividends by 1000, in the case of Belgium, Czech Republic, Greece, Ireland, the Netherlands, Portugal, Slovakia, Spain, the U.K. and the US we divide dividends by 100, in the case of Luxembourg we divide dividends by 30 and in the case of Austria, Denmark, Finland, France, Germany, Norway, Poland, Sweden and Switzerland we divide dividends by 10.

[43] Note that the lists FUSAA-FUSAG contain the same information as the FAMERA-FAMERZ lists, employed by Ince and Porter (2006, p. 465). However, FUSAA-FUSAG comprise only seven instead of twenty-six lists.

[44] The lists “FUSAA, FUSAB, …, FUSAG”, “DEADUS1, DEADUS2, …, DEADUS6” and “WSUS1, WSUS2, …, WSUS18” are special constituent list of all available firms availiable provided by Thomson Reuters Datastream and Thomson Reuters Worldscope.

[45] In the updated sample we use the following Wordscope lists in addition: WSUS19, WSUS20, WSUS21.

A.1.2. Constituent lists for the International sample

We collect data from the following lists: WSCOPEOE, ALLAS, DEADOE (Austria); WSCOPEBG, FBDO, DEADBG (Belgium); WSCOPEDK, FDEN, DEADDK (Denmark); WSCOPEFN, FFIN, DEADFN (Finland); WSCOPEFR, FFRA, ALLFF, DEADFR (France); WSCOPEBD, FGER1, FGER2, DEADBD1, DEADBD2 (Germany), WSCOPEIR, FIRL, DEADIR (Ireland); WSCOPEIT, FITA, DEADIT (Italy); WSCOPENL, FHOL, ALLFL, DEADNL (Netherlands); WSCOPENW, FNOR, DEADNW (Norway); WSCOPEPT, FPOM, FPOR, FPSM, DEADPT (Portugal); WSCOPEES, FSPN, DEADES (Spain); WSCOPESD, FSWD, DEADSW (Sweden); WSCOPESW, FSWS, DEADSW (Switzerland); WSCOPETK, FTURK, DEADTK (Turkey); WSCOPEUK, FBRIT, DEADUK (U.K.); WSCOPELX, FLUX, DEADLX (Luxembourg); WSCOPEGR, FGREE, FGRPM, FGRMM, FNEXA, DEADGR (Greece); WSCOPEHN, FHUN, DEADHU (Hungary); WSCOPEPO, FPOL, DEADPO (Poland); WSCOPECZ, FCZECH, FCZECHUP, DEADCZ (Czech Republic); FSLOVAK, FSLOVALL, DEADSLO (Slovakia); WSCOPEIC, FICE, DEADIC (Iceland); WSCOPEJP, JAPALL (Japan); WSCOPEHK, HGKG, DEADHK (Hong Kong); WSCOPESG, FSINQ (Singapore); WSCOPEAU, FAUS, DEADAU (Australia); WSCOPECN, LTTOCOMP, DEADCN1, DEADCN2 (Canada).

These lists are basically selected from three categories: Worldscope lists, research lists and dead lists. Worldscope lists begin with "WSCOPE" or "WS" and end with a two-letter country code. Worldscope lists exist for all countries employed in this study, except Slovakia. Research lists aim to cover all equities listed in a specific country. Datastream provides two kind of those lists. The first kind begins with "ALL" and ends with a two-letter country code. The second kind begins with "F" and ends with a three-to-five letter country code. For all countries at least one of these lists is provided by TRD and TRW. Dead lists are used to keep the sample free of a survivorship bias, since the other lists typically contain only active stocks. Dead list begin with "DEAD" and end with a two-letter country code. Dead list exist for all countries employed in this study, except Japan.[46]

[46] Since dead stocks are also includec in Worldscope lists, we don't think this is an serious issue.

Besides these three list types we use additional lists for some countries. These lists are either main market lists (Portugal, Greece), second market lists (Portugal), or new market lists (NEXA - Greece). In addition, we use the FCZECHUP list in case of the Czech Republic.

A.2. Common risk factors

This section describes the constuction of common risk factors as proposed by Fama and French (1993) and Carhart (1997) (Section A.2.1) as well as the calculation of breakpoints for the allocation of stocks to portfolios employed in this paper (Section A.2.2). Moreover in Section A.2.3 we compare portolios sorted on size, BE/ME and momentum with the corresponding portolios provided by Kenneth French. Section A.2.4 evaluates the usefulness of the dynamic screens.

A.2.1. Construction

Fama and French (1993) introduced common risk factors based on individual stock characteristics. To obtain market-wide factors from individual firm characteristics, Fama and French (1993) sorted stocks on these characteristics and used the difference in portfolio returns between high rated and low rated stocks according to these characteristics. In particular, they proposed one factor based on the difference in portfolio returns between stocks with a small market capitalization and stocks with a big market capitalization (small-minus-big – SMB) and one factor based on the difference between stocks with a high book-to-market equity ratio and a low book-to-market equity ratio (high-minus-low – HML) in addition to the market factor. This empirical model has become standard in the empirical asset pricing literature. Following the recipe of Fama and French (1993) other factors based on individual stock characteristics have been proposed in the literature, most notably the momentum factor proposed by Carhart (1997), which is based on the observation by Jegadeesh and Titman (1993) that stocks with a high past performance (winners) outperform stocks with a low past performance (losers) in the next 3-12 months.

This factor is based on the difference between winner and loser portfolios and is often referred to as WML (winners-minus-losers). We follow this method to construct the factors SMB, HML and WML.

Our TRD and TRW dataset of monthly observations begins in December 1985 and ends in February 2012.[47] The return calculation is based on closing prices of the last trading day of each month. If a stock is not traded on the last trading day, the last valid trading price is used. The TRD total return indices which we use for return calculation include dividends and account for stock splits.

Book equity is TRW 'common equity' (WC03501) in our dataset. For sorts utilizing book equity we use only stocks with available book equity which is greater than zero. Size is either the TRD 'market value' (MV) or the product of the TRD 'unadjusted price' (UP) with the TRD 'number of shares' (NOSH). BE/ME for the sorting month June is calculated as book equity of the previous fiscal year divided by size of the preceding December. For the construction of the SMB and HML factors, we sort all stocks each June, beginning in 1986. To be included in the June sort of year τ a stock must have an available and positive book value and size available in December of the previous year $\tau\text{-}1$. Furthermore, to calculate value weighted returns, a stock needs to have available size from the preceding month, a valid return, an available and positive book value, as well as 'price' available and 'number of shares' different from zero.[48]

In order to construct the SMB and HML factors, all remaining stocks are sorted each December into three BE/ME groups (breakpoints are discussed in Section A.2.2). Furthermore, we sort these stocks each June into two size groups. From the intersection of the two size groups, small (S) and big (B), and the three BE/ME groups, low (L), medium (M) and high (H), we form six portfolios, which are held for one year.[49] Panel A of Table A.10 illustrates the sorting procedure.

[Table A.10 here]

[47] Note that we therefore begin with the porfolio formation in June 1986 and with the calculation of return series in July 1986. This applies only to the US dataset. For other countries a different time span is used.

[48] For sorts which do not utilize book equity, we do not require that book value is available and positive. However, certainly the characteristic on which the sorting is done has to be available in additon to the other mentioned requirements.

[49] When a stock is no longer available in our dataset we invest the share of this stock into the other stocks in the respective portfolio group according to the employed weighting scheme.

From the monthly value weighted returns of these six portfolios we construct the factors SMB and HML for month t as follows:

$$\mathrm{SMB}_t = \frac{r_t^{S/L} + r_t^{S/M} + r_t^{S/H}}{3} - \frac{r_t^{B/L} + r_t^{B/M} + r_t^{B/H}}{3}, \tag{A.1}$$

$$\mathrm{HML}_t = \frac{r_t^{S/H} + r_t^{B/H}}{2} - \frac{r_t^{S/L} + r_t^{B/L}}{2}. \tag{A.2}$$

$r_t^{X/Y}$ denotes the returns of a portfolio of stocks belonging to size class X (either S or B) and BE/ME class Y (either H, M or L) in month t based on the portfolio formation in last June.

In order to construct the momentum factor, we first define the momentum measure which we employ in this paper and is commonly used in the literature (e.g. Fama and French, 2012). For each portfolio-formation month t-1 we calculate for each stock the mean return from month t-12 to month t-2 and use this mean return to compile three momentum groups. This sorting takes place every month. We also construct two size groups each month. To be included in the sort, the stock return has to be available in every month from t-12 to t-2 and size must be available in month t-1. From the intersection of the two size groups, i.e. small (S) and big (B), and the three momentum groups losers (L), medium (M) and winners (W), we form six portfolios. The sorting procedure is illustrated in panel B of Table A.10.

We construct the factor WML for month t as the difference of the mean returns of the two winner portfolios minus the mean returns of the two loser portfolios:

$$\mathrm{WML}_t = \frac{r_t^{S/W} + r_t^{B/W}}{2} - \frac{r_t^{S/L} + r_t^{B/L}}{2}. \tag{A.3}$$

$r_t^{X/Z}$ denotes the returns of a portfolio of stocks belonging to size class X (either S or B) and momentum class Z (either W, M or L) in month t based on the portfolio formation in month t-1.

A.2.2. Choice of breakpoints

In each of the above sorts, we need to choose breakpoints to divide the stocks into different portfolios. This issue is most relevant for the size breakpoints and arises to a lesser extent for the BE/ME and momentum sorts. With respect to size in the US, Fama and French (1993, p. 8) calculate breakpoints from the NYSE sample only, but apply the breakpoints to the whole sample of NYSE, AMEX, and NASDAQ stocks.[50] The rationale behind this procedure is to limit the influence of microcaps and small stocks (see also Hou, Xue and Zhang, 2012). Unfortunately, it is impossible to separate the NYSE stocks in our sample from other stocks (at least not over the whole time span). Therefore, we use an approximation by using breakpoints calculated from the whole sample, but aiming to mirror the Fama and French (1993) NYSE breakpoints. By considering the number of firms in each of the six size-BE/ME portfolios reported on Kenneth French's website, we can calculate the average of the empirical breakpoints which separates small and big stocks in those portfolios. Panel A of Table A.11 shows the corresponding results. The mean (median) of this breakpoint is the 0.81 (0.81) quantile for the period from 07/1986 to 02/2012. Furthermore, the minimum of this breakpoint is the 0.76 quantile and the maximum is the 0.84 quantile, which suggests that this breakpoint is quite stable over time. Therefore, we use in our application the 0.80 quantile as a breakpoint for the separation of small and big stocks. The empirical mean (median) FF breakpoints for the BE/ME portfolios are the 0.35 (0.35) and 0.70 (0.70) quantiles. For the seperation among the three BE/ME groups we use the 0.30 respectively the 0.70 quantiles. The breakpoints actually used are reported in the "actual" column of Table A.11. We do not use exactly the mean or median empirical breakpoints since the breakpoints we actually employ are more common in similar applications and are roughly close to the mean or median empirical breakpoints. We apply this approximation procedure to all portfolios involving size. Panel B of Table A.11 shows the breakpoints implied by the FF data for the size-momentum sort into six portfolios.

[Table A.11 here]

[50] NYSE breakpoints are also freqently used by other researchers. For example, Ang and Chen (2002, p. 455) and Adrian and Franzoni (2009, p. 540) calculate breakpoints from all NYSE stocks and sort all stocks on NYSE, AMEX, and NASDAQ into portfolio groups according to the NYSE breakpoints. Campbell (1996, p. 316-317), Chen et al. (1986, p. 394-395), Cochrane (1996, p. 587), and Ferson and Harvey (1991, p. 391) use size portfolios constructed from NYSE stocks.

In addition, we also report in the same manner as described above the breakpoints for the ten US size portfolios (Table A.12), the ten US BE/ME portfolios (Table A.13), the ten US momentum portolios (Table A.14), the 25 US size and BE/ME portfolios (Table A.15) and the 25 size and momentum portfolios (Table A. 16).

[Tables A.12—A.16 here]

A.2.3. Portfolios sorted on size, BE/ME, and momentum

To further evaluate the quality of our dataset, we sort all stocks separately on the characteristics size, BE/ME, and momentum. We compare the individual portfolios of each sort with portfolios provided by Kenneth French. We report means, standard deviations, and correlation coefficients of the average monthly returns over time of the corresponding portfolios.

First, we sort all stocks in our dataset according to their size and allocate them into ten size groups according to the empirical breakpoints inferred from the FF data, as described in Appendix A.2.2 (see also Table A.12). The results are shown in Table A.17. The correlation coefficients, ranging between 0.92 and 0.94, show that the returns of our size portfolios behave very similarly to the returns of the FF size portfolios.

Note also that the average stock returns for the ten size groups are very similar for the FF and our TRD and TRW datasets. The only exception is the smallest group, in which the average return in the FF dataset exceeds the average returns of our dataset by about 0.2 percentage points per month, suggesting the presence of an “inverted size effect” (Fama 1991, p. 1588) in our data.

Next, we consider the results for the ten BE/ME groups. Here, we form portfolio groups by employing decile breakpoints (see also Table A.13). The results are also shown in Table A.17. The average returns for the ten FF BE/ME groups are approximately increasing in BE/ME. We observe the same behavior for our ten TRD and TRW BE/ME groups. The correlations are somewhat smaller than in the case of the size groups, but still very high, ranging from 0.82 to 0.92.

Table A.17 also shows the same figures for the ten momentum group groups, again by employing decile breakpoints (see Table A.14). The ten momentum groups of each dataset show an almost monotonic behavior between momentum and average returns. The average return of the tenth group for our dataset is substantially higher than the average returns in the FF dataset. The correlations of the momentum groups range between 0.84 and 0.92.

[Table A.17 here]

Next, we compare our TRD and TRW portfolios with the FF portfolios sorted on two characteristics jointly. Overall, our twenty-five portfolios sorted on size-BE/ME and size-momentum are quite similar to the corresponding FF portfolios when evaluated in terms of return correlations. There are some notable differences in average returns, though.

Panel A of Table A.18 shows the detailed results. For most of the size groups there seems to be a positive monotonic relation between BE/ME and average returns. However, for the BE/ME groups we observe a different behavior regarding size, depending on the specific group. For low BE/ME stocks, we find an inverted size effect, which means that big firms yield higher average returns than small firms. However, this effect is much more pronounced in the FF dataset. Thus, the biggest difference in the average returns of our TRD and TRW and FF size-BE/ME return series can be found in the small size/low BE/ME group.[51] For the second and third BE/ME group there seems to be no relation between size and average returns. In the fourth and the highest BE/ME group a size effect with high returns in the small size

[51] It is not clear why these differences emerge. The number of stocks for our TRD and TRW data is considerably smaller from the beginning of the sample up to mid 1999 (up to about 2500 stocks bigger). One would assume that this difference is mostly due to smaller stocks which are in the FF dataset but not in our data. Therefore, using roughly the same breakpoints would shift big stocks from each bigger portfolio to the next smaller one, resulting, for example, in higher average returns for the smaller portfolios of the TRD/TRW data, compared to the FF portfolios in case of the low BE/ME stocks. On the other hand from mid 1999 on, the number of stocks in our dataset is considerably bigger than the number of stocks in the FF data (up to about 1500 stocks bigger) and therefore the small portfolios may be dominated by small OTC stocks. Since these stocks are known to underperform listed stocks (e.g. Ang et al., 2013) small portfolios in our data may underperform small FF portfolios, as it is the case with the size deciles in Table 2. In addition, since we do not require book values to be available for the size sorts, the small OTC stocks might have even a bigger influence on the mean returns than for the portfolios sorted on size and BE/ME.

groups and low returns in the big size groups can be observed in both datasets. The correlations of our 25 TRD and TRW size-BE/ME portfolios with the 25 FF size-BE/ME portfolios range between 0.82 (big size/high BE/ME-portfolio) and 0.95 (small size/low BE/ME, small size/second lowest BE/ME and small size/high BE/ME-portfolios).

[Table A.18 here]

We report the results for 25 size-momentum portfolios in panel B of Table A.18. In case of the FF portfolios, we observe an "inverted size effect" in the loser and the second momentum group (but rather weak) and a size effect in the third, fourth, and winner groups. For our TRD and TRW size-momentum portfolios we observe a similar pattern. In each of the size groups we observe a momentum effect, which means that the average returns of the winner portfolio are always higher than the average returns of the looser portfolio. The correlations of the twenty-five size-momentum returns between the two dataset range between 0.87 and 0.95.

In sum, this benchmark exercise confirms that TRD and TRW data can be used to construct test portfolios, sorted on single characteristics as well as joint sorts on two characteristics which are similar to the Kenneth French versions. While this is not surprising per se, it is a comforting baseline result that increases confidence in the ability to construct accurate test portfolios also for other countries across the globe.

A.2.4. Are the detailed screens necessary?

Another important question is whether the advanced screens applied for our dataset in this paper are really necessary or if simpler ones perform just as well. To answer this question we alternatively apply a very simple screening procedure and just eliminate returns above 300% as well as the outliers as indicated in footnote 27 in Section A.1.[52] The results for the US factors are shown in Panel A of Table A.19. The market portfolio as well as the SMB and HML factors from simple screens are remarkably close to the FF versions and the versions from the advanced screens. However, the correlation of the simple WML factor with the FF version is clearly lower than the correlation of the WML version from advanced screens. In addition, the standard deviation of the WML factor with simple screens is higher than the standard deviation of the FF and advanced screens WML factor versions. This standard deviation is so high that the simple WML factor is not different from zero ate the 10% significance level.

We also compute the ten size, BE/ME and momentum deciles from the simply screened data. The outcome is shown in Panel B of Table A.19. The bottom line is the same as from the results with factor data. The main differences compared to the advanced screen data occur for momentum. The decile with the lowest returns over the past 2-12 month has the lowest correlation with the same decile from FF data, amounting only to 0.59.

In sum, the simple screens seem to perform reasonably well for the value and size factors, but rather poorly when it comes to momentum. As momentum is an important anomaly which is examined in many research papers and which serves as an important control when assessing long-term excess returns, we recommend not to use such simple screens in general.

[Table A.19 here]

A.3. Dataset Updates

A first version of this paper contained data up to 2009. Since a longer time series can considerably improve the power of asset pricing tests (see the discussions in Campbell et al. (1997, p. 204-207) and Cochrane (2005, p. 286-291)), we updated the dataset for this new version of the paper. However, the

[52] In addition, we already applied the static screens SS01-SS03 before even downloading the time series data. Thus, this exercise is an illustration of the usefulness of the dynamic screens.

updating procedure is not a straightforward task and there are some important points which have to be adressed. First of all one has to decide if the whole dataset is drawn complety new from TRD or if only the newly accumulated data since the last drawing procedure. Both possibilities have their pros and cons. We decided to update the dataset sequentially (that is, to draw only the newly accumulated data). Our reasons for doing so are as follows: First, this practice is much faster than to update the dataset completely new. Second, a sequential updating procedure might provide valuable insight to the time series behaviour of the static dataset items (e.g. exchange listing, industry affiliation, …) which has at least indirect implications for the dataset (e.g. we assumed in a first version of this paper that using firms end-of-sample exchange affiliation would result in a biased sample. Due to the static information from two different points in time we can therefore observe now that some firms which had been listed on a major exchange (e.g. NYSE) in the first draw, are in the second draw listed on a small exchange (e.g. OTC). However, this observation does not directly confirm that relying on the exchange affilition would induce a serious bias, but at least it gives an hint that this might be an issue one has to take care.).

For the sequential update one has to draw at first the static information from the Datastream/Worldcope lists (see Sections A.1 and A.2) as in the initial drawing. The reason for this is that the lists are constantly updated and relying on the old static lists would ignore newly added firms. Before applying the time series screens, we merge the new and the old dataset. Thereby we adjust the price and total return index series of the old dataset if the last price/total return index observation of the old dataset and the first price/total return index observation of the new dataset are different (we draw the new data so that the first observation coincides at least on the same date as the last observation of the old dataset). This procedure ensures that no flawed return rates due to stock splits or other firm events are induced. Table A.20 lists the time span of the first and second drawing procedure. All draws begin in January 1980, but many countries have valid observations only from a later date on.

[Table A.20 here]

A.4. Riskfree Interest Rate Proxy

Another important issue for an international financial dataset is the choice of an appropriate proxy for the riskfree interest rate. One important characteristic for choosing such an instrument is that it has no default risk (Damodaran, 2008, p. 6). Usually in asset pricing studies a 1 or 3 month Treasury bill is used (e.g. Fama and French, 1993 or Dimson and Marsh, 2001). However, a 1 or 3 month Treasury bill is only for a minority of the countries in this study available. But other possible proxies for the riskfree interest rate are available. In this paper we consider two candidates: the 3 month overnight indexed swap (OIS) (e.g. Filipović and Trolle, 2013) as well as the 1 or 3 month interbank rate (IBR) (e.g. Bauer et al., 2010). However, both candidates have serious drawbacks. Since the onset of the financial crisis in August 2007 there seems to be default risk incorporated into the IBR and therefore it is much higher than other riskfree rate proxies (see Filipović and Trolle, 2013, p. 707 and fig. 1). Before then the IBR seems to behave similar as the Treasury bill. On the other hand the OIS for the countries in our sample is only available since the year 2000. Therefore none of these two proxies alone seems to be an eligible candidate. To overcome this problem we suggest the following: Before the OIS is available we use the IBR. When both, the OIS and the IBR are available, we use the minimum of both rates as our measure of the riskfree rate.

To illustrate the arguments put forth above, we look at the Treasury bill, the OIS and the IBR, for the US, the UK and France. The time series graphs of these series are shown in Figure A.1.

[Figure A.1 here]

The upper left panel shows the graph for the US. The treasury bill has usually the smallest magnitude (there are a few exeptions in 2004 were the OIS is sometimes smaller), the OIS is often of a similar magnitude (the exception is the 2006-2009 period where the OIS is sometimes considerably higher than the treasury bill, but still lower than the IBR), whereas the IBR is close to the other two series until early 2006 but is much higher afterwards. The spike of the IBR in October 2008 is notable. In September 2008

Lehman Brothers became bancrupt and obviously default risk became priced in the IBR. Thereafter the IBR decreased but was still higher relative to the other two rates than before 2006.

The evolution of the three series for the UK and France, respectively are largely similar. Up to the emergence of the subprime crisis in August 2007 the three series move closely together. Afterwards the IBR is considerably higher. In both countries the OIS moves similar as the treasury bill, also after August 2007.

Because of these observations we therefore argue that before 2007 the IBR seems to be a good proxy for the riskfree rate when there is no treasury bill available. On the other hand we argue that the OIS seems to be a valid alternative for the treasury bill and should be used in general when there is no treasury bill available. However, observations for the OIS are not available before the year 2000 and therefore we suggest to use a combination of the IBR and the OIS as stated above. Table A.21 provides an overview of the riskfree rate proxies eventually used in the dataset. Several pecularities are mentionable. First, for Japan we use the short term money market rate as provided by the Bank of Japan. The reason for this is that our first choice the Gensaki 1 month T-Bill is only available since 1993 on Datastream. Since the money market rate from the Bank of Japan is very similar the Gensaki 1 month T-Bill, we use the longer series to obtain a longer time series (The series from the Bank of Japan is available since 1985). Second, in one case (Norway) we combine the IBR with the treasury bill (not the OIS) because the treasury bill is only available after 2002. Third, for Turkey only the IBR is available and is therefore used due to the lack of a better alternative proxy. Finally, for the Euro-countries where no OIS is available, we use the OIS of the Euro zone, as indicated in the 'Euro OIS' column.

[Table A.21 here]

A.5. Market capitalization of countries used in this study as by June 2011

[Tables A.22 here]

A.6. Portfolio turnover and trading volume of the size spread portfolios

[Tables A.23 — A.24 here]

Appendix References

Adrian, T., Franzoni, F., 2009. Learning about Beta: Time-varying Factor Loadings, expected returns, and the conditional CAPM. Journal of Empirical Finance 16, 537–556.

Ang, A., Chen, J., 2002. Asymmetric Correlations of Equity Portfolios. Journal of Financial Economics 63, 443–494.

Ang, A., Shtauber, A.A., Tetlock, P.C., 2013. Asset Pricing in the Dark: The Cross-Section of OTC Stocks. Review of Financial Studies 26, 2985–3028.

Bauer, R., Cosemans, M., Schotman, P.C., 2010. Conditional Asset Pricing and Stock Market Anomalies in Europe. European Financial Management 16, 165-190.

Campbell, C.J.., Cowan, A.R., Salotti, V., 2010. Multi-country event-study methods. Journal of Banking and Finance 34, 3078-3090.

Campbell, J.Y., Lo, A.W., MacKinlay, A.C., 1997. The Econometrics of Financial Markets. Princeton University Press, Princeton.

Carhart, M.M., 1997. On Persistence in Mutual Fund Performance. The Journal of Finance 52, 57–82.

Chen, N.-F., Roll, R., Ross, S.A., 1986. Economic Forces and the Stock Market. The Journal of Business 59, 383–403.

Cochrane, J.H., 1996. A Cross-Sectional Test of an Investment-Based Asset Pricing Model. The Journal of Political Economy 104, 572–621.

Cochrane, J.H., 2005. Asset Pricing, revised edition. Princeton University Press, Princeton.

Damodaran, A., 2008. What is the riskfree rate? A Search for the Basic Building Block. Mimeo, Stern School of Business, New York.

Dimson, E., Marsh, P., 2001. U.K. Financial Market Returns, 1955—2000. The Journal of Business 75, 1–31.

Fama, E.F., 1991. Efficient Capital Markets: II. The Journal of Finance 46, 1575–1617. Fama, E.F., French, K.R., 1993. Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics 33, 3–56.

Fama, E.F., French, K.R., 2012. Size, Value and Momentum in International Stock Returns. Journal of Financial Economics 105, 457–472.

Ferson, W.E., Harvey, C.R., 1991. The Variation of Economic Risk Premiums. The Journal of Political Economy 99, 385–415.

Filipović, D., Trolle, A.B., 2013. The Term Structure of Interbank Risk. Journal of Financial Economics 109, 707-733.

Hou, K., Xue, C., Zhang, L., 2012. Digesting Anomalies: An Investment Approach. Working Paper.

Ince, O.S., Porter, R.B., 2006. Individual Equity Return Data from Thomson Datastream: Handle with Care! The Journal of Financial Research 29, 463–479.

Jegadeesh, N., Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance 48, 65–91.

Lee, K.-H., 2011. The World Price of Liquidity Risk. Journal of Financial Economics 99, 136-161.

Thomson Financial, 2007. Worldscope Database: Datatype Definitions Guide. Issue 6.

Ulbricht, N., Weiner, C., 2005. Worldscope Meets Compustat: a Comparison of Financial Databases. Working Paper, Humboldt University Berlin.

Table A.1: Static screens

Screen identifier	Short description	Items involved
SS01	We delete all firms which are not indicated as major listings.	Major Security Flag
SS02	We delete all firms which are not located on the domestic market.	Geography Group Name
SS03	We delete all stocks which are not of the equity type.	Type of Instrument
SS04	All stocks are excluded which are not listed on domestic exchanges	Exchange Mnemonic
SS05	We search the Extended Name for suspicious word parts and set, the returns to missing (cf. Ince and Porter, 2006, p. 471 and Campbell et al., 2010, p. 3089).	Extended Name

Table A.2: Dynamic screens

Screen identifier	Short description	Items involved
DS01	We delete all zero returns (with returns calculated from the total return index) from the end of the sample until the first non-zero return (cf. Ince and Porter, 2006, p. 465).	Total Return Index
DS02	We delete all zero values (with returns calculated from the price index) from the end of the sample until the first non-zero value (cf. Ince and Porter, 2006, p. 465).	Price Index
DS03	We delete all so-called "Penny-stocks" with (unadjusted) prices less than the 5 per cent quantile of the domestic price distribution over the whole sample period (cf. Ince and Porter, 2006, p. 473 or Lee, 2011, p. 140. Ince and Porter remove observations with end of month prices below 1 US$. Lee removes observations with end of year prices below the 2.5 per cent quantile. For example, Ince and Porter report that removing prices below 0.1 US$ works almost as well as the 1 $ threshold.).	Unadjusted Price
DS04	We set all returns to missing for which the price is greater than 1,000,000 of the domestic currency.	Price Index
DS05	We divide all dividends by a fixed value, which are greater than half the adjusted price (a detailed treatment on this issue is given in Section A.1).	Price Index, Dividends
DS06	If there are no observations in the total return index, then price and dividend (if available) information are used to compile returns, if at least price information is available.	Total Return Index, Price Index, Dividends
DS07	We compare the Thomson Reuters Datastream total return index with the self-created total return index constructed from price and dividend (if available) data and use the self-created index if the difference between the total return index is greater than 0.5 in absolute terms (cf. Ince and Porter, 2006, p. 473).	Total Return Index, Price Index, Dividends
DS08	We compare the Thomson Reuters Datastream market value with the self-created market value, calculated by multiplying the unadjusted price with the number of shares and set the market value to missing if the difference in terms of the self-created market value is greater than 0.5 in absolute terms.	Total Return Index, Price Index, Market Value, Dividends
DS09	We set all returns to missing, for which the return is greater than 990%.	Return
DS10	We delete the returns for which R_t or R_{t-1} is greater than 300% and $(1+R_t)(1+R_{t-1})-1$ is less than 50% (cf. Ince and Porter, 2006, p. 473-474, fn. 4).	Total Return Index

Table A.3: Number of firms for the US market

Year	List	Corrected	Market	SMB/HML	WML
1984	4,702	4,105	2,839	1,822	2,542
1985	5,014	4,266	2,994	1,928	2,838
1986	5,590	4,630	3,229	2,038	2,978
1987	6,489	5,316	3,541	2,145	3,172
1988	7,026	5,827	3,714	2,353	3,466
1989	7,460	5,843	3,812	2,513	3,625
1990	7,921	5,774	3,930	2,487	3,726
1991	8,323	5,854	4,094	2,501	3,884
1992	9,015	6,047	4,441	2,795	4,023
1993	9,739	6,434	4,822	2,963	4,392
1994	10,851	7,297	5,496	3,288	4,781
1995	11,620	7,536	5,860	4,401	5,389
1996	13,069	8,429	6,630	4,959	5,743
1997	14,833	9,410	7,478	5,628	6,516
1998	16,537	10,279	8,161	5,975	7,197
1999	17,840	10,815	8,483	6,786	7,741
2000	20,247	12,122	9,215	7,091	7,901
2001	21,061	11,876	8,988	6,943	8,468
2002	22,010	11,434	8,758	6,329	8,257
2003	22,749	10,748	8,507	6,097	8,116
2004	23,742	10,934	8,535	5,899	8,114
2005	24,844	11,253	8,639	5,944	8,091
2006	25,632	11,494	8,735	5,864	8,198
2007	26,513	11,383	8,642	5,724	8,150
2008	27,251	11,176	8,489	5,623	8,004
2009	28,033	10,738	8,283	4,383	7,852
2010	28,540	10,666	8,161	5,192	7,837
2011	28,933	10,131	7,653	4,965	7,523
All	29,150	26,034	15,239	14,129	15,238

Note: We report the number of firms for different stages of the data preparation process. The numbers shown correspond to July for each year. The "List" column refers to the number of firms for the list which we use to draw time series data. This list is already corrected for static items, which are foreign stocks, non-equities, and additional listings as described in Section 2.1. In addition, we require the dscd code (DSCD), common equity (WC03501), fiscal year end (WC05350) and prices (P) to be non-missing, which are minimum requirements to be included in the portfolio sorts. The "corrected" column refers to the number of firms after the time series screens depicted in Table A.2. The same minimum requirements as for the "list" stocks are also imposed. The "Market", "SMB/HML" and "WML" columns report the number of firms which are actually used to compile the Market Return, the SMB and HML factors and the WML factor. Note that these numbers refer to the value weighted case. The "All" row reports the number of unique firms observed over the whole time span.

Table A.4: Number of firms for the European market

Year	List	Corrected	Market	SMB/HML	WML
1984	3,490	2,707			
1985	3,718	2,784			
1986	4,108	3,025	1,904		
1987	4,550	3,288	2,171	961	
1988	5,288	3,784	2,650	1,632	2,163
1989	6,481	4,720	3,392	2,340	2,628
1990	6,917	4,914	3,642	2,855	3,371
1991	7,342	5,074	3,902	3,131	3,619
1992	7,627	5,029	4,020	3,215	3,826
1993	7,874	4,988	4,103	3,282	3,936
1994	8,444	5,326	4,354	3,448	4,043
1995	9,054	5,563	4,631	3,579	4,269
1996	9,580	5,731	4,883	3,672	4,530
1997	10,353	6,062	5,272	4,437	4,769
1998	11,115	6,336	5,658	4,844	5,117
1999	11,917	6,512	5,920	5,040	5,305
2000	13,022	6,887	6,212	5,261	5,509
2001	13,919	7,140	6,404	5,701	5,800
2002	14,509	6,899	6,226	5,574	5,954
2003	14,709	6,428	5,887	5,257	5,706
2004	15,114	6,344	5,839	5,118	5,578
2005	15,776	6,513	6,034	5,206	5,547
2006	16,596	6,802	6,334	5,490	5,713
2007	17,454	7,128	6,618	5,841	6,012
2008	18,081	7,050	6,491	5,875	6,102
2009	18,661	6,795	6,178	5,391	5,924
2010	18,969	6,476	5,922	5,520	5,714
2011	18,952	6,295	5,691	5,401	5,604
All	20,031	17,429	11,315	11,239	11,310

Note: We report the number of firms for different stages of the data preparation process. The numbers shown correspond to July for each year. The "List" column refers to the number of firms for the list which we use to draw time series data. This list is already corrected for static items, which are foreign stocks, non-equities, and additional listings as described in Section 2.1. In addition, we require the dscd code (DSCD), common equity (WC03501), fiscal year end (WC05350) and prices (P) to be non-missing, which are minimum requirements to be included in the portfolio sorts. The "corrected" column refers to the number of firms after the time series screens depicted in Table A.2. The same minimum requirements as for the "list" stocks are also imposed. The "Market", "SMB/HML" and "WML" columns report the number of firms which are actually used to compile the Market Return, the SMB and HML factors and the WML factor. Note that these numbers refer to the value weighted case. In the equal weighted case the numbers would be slightly higher, since the size values of the preceding month are not needed. The "All" row reports the number of unique firms observed over the whole time span. Note that the "European" sample is composed of all European OECD countries.

Table A.5: Number of firms for the Japanese market

Year	List	Corrected	Market	SMB/HML	WML
1984	919	916	916	607	916
1985	920	919	919	583	917
1986	922	920	920	742	918
1987	924	921	921	838	919
1988	1,521	1,517	1,515	939	920
1989	1,674	1,662	1,660	1,077	1,514
1990	2,130	2,069	2,066	1,227	1,659
1991	2,303	2,295	2,291	1,611	2,064
1992	2,412	2,390	2,386	1,955	2,290
1993	2,476	2,456	2,451	2,029	2,379
1994	2,615	2,581	2,577	2,084	2,448
1995	2,815	2,775	2,770	2,195	2,566
1996	2,979	2,940	2,935	2,267	2,769
1997	3,126	3,081	3,072	2,333	2,923
1998	3,249	3,138	3,130	2,334	3,002
1999	3,341	3,230	3,219	3,059	3,114
2000	3,489	3,254	3,237	3,017	3,041
2001	3,688	3,337	3,324	3,104	3,126
2002	3,870	3,284	3,275	3,115	3,097
2003	3,992	3,444	3,430	3,195	3,206
2004	4,139	3,597	3,593	3,413	3,433
2005	4,323	3,716	3,709	3,552	3,523
2006	4,518	3,832	3,820	3,629	3,618
2007	4,696	3,899	3,881	3,716	3,684
2008	4,770	3,813	3,784	3,701	3,686
2009	4,813	3,631	3,615	3,490	3,503
2010	4,840	3,465	3,451	3,396	3,415
2011	4,876	3,424	3,385	3,352	3,364
All	4,959	4,944	4,827	4,823	4,826

Note: We report the number of firms for different stages of the data preparation process. The numbers shown correspond to July for each year. The "List" column refers to the number of firms for the list which we use to draw time series data. This list is already corrected for static items, which are foreign stocks, non-equities, and additional listings as described in Section 2.1. In addition, we require the dscd code (DSCD), common equity (WC03501), fiscal year end (WC05350) and prices (P) to be non-missing, which are minimum requirements to be included in the portfolio sorts. The "corrected" column refers to the number of firms after the time series screens depicted in Table A.2. The same minimum requirements as for the "list" stocks are also imposed. The "Market", "SMB/HML" and "WML" columns report the number of firms which are actually used to compile the Market Return, the SMB and HML factors and the WML factor. Note that these numbers refer to the value weighted case. In the equal weighted case the numbers would be slightly higher, since the size values of the preceding month are not needed. The "All" row reports the number of unique firms observed over the whole time span.

Table A.6: Number of firms for the Hong Kong market

Year	List	Corrected	Market	SMB/HML	WML
1984	92	88			
1985	103	99			
1986	107	100			
1987	126	116			
1988	259	236			
1989	284	264			
1990	294	261			
1991	317	279			
1992	374	331	180		
1993	438	396	218		
1994	500	456	245	4	216
1995	523	477	268	12	245
1996	556	501	285	42	269
1997	617	553	304	63	285
1998	663	580	317	70	294
1999	688	603	329	67	322
2000	750	649	366	67	321
2001	832	692	430	123	350
2002	928	752	498	220	410
2003	988	754	516	276	450
2004	1'042	815	574	327	521
2005	1'084	871	627	359	580
2006	1'136	927	651	379	624
2007	1'192	1'014	692	404	680
2008	1'254	1'060	697	397	674
2009	1'277	1'072	700	391	684
2010	1'349	1'132	713	386	693
2011	1'435	1'195	724	377	698
All	1,543	1,523	802	790	802

Note: We report the number of firms for different stages of the data preparation process. The numbers shown correspond to July for each year. The “List” column refers to the number of firms for the list which we use to draw time series data. This list is already corrected for static items, which are foreign stocks, non-equities, and additional listings as described in Section 2.1. In addition, we require the dscd code (DSCD), common equity (WC03501), fiscal year end (WC05350) and prices (P) to be non-missing, which are minimum requirements to be included in the portfolio sorts. The “corrected” column refers to the number of firms after the time series screens depicted in Table A.2. The same minimum requirements as for the “list” stocks are also imposed. The “Market”, “SMB/HML” and “WML” columns report the number of firms which are actually used to compile the Market Return, the SMB and HML factors and the WML factor. Note that these numbers refer to the value weighted case. In the equal weighted case the numbers would be slightly higher, since the size values of the preceding month are not needed. The “All” row reports the number of unique firms observed over the whole time span.

Table A.7: Number of firms for the Singapore market

Year	List	Corrected	Market	SMB/HML	WML
1984	98	95	95		
1985	102	100	100		
1986	103	101	101		
1987	111	106	106	32	101
1988	120	116	116	38	106
1989	128	124	124	44	116
1990	135	130	130	49	124
1991	152	148	148	57	130
1992	167	162	162	91	148
1993	185	178	178	107	162
1994	210	203	202	111	178
1995	233	226	225	132	202
1996	251	242	241	190	225
1997	286	275	274	213	240
1998	311	299	298	225	272
1999	340	317	316	225	292
2000	413	380	377	235	308
2001	476	431	425	352	361
2002	501	440	436	402	406
2003	544	457	456	417	416
2004	611	512	509	452	443
2005	684	561	557	508	480
2006	741	598	593	534	535
2007	781	653	645	598	603
2008	838	668	664	628	612
2009	851	634	630	608	605
2010	889	643	634	608	599
2011	915	635	612	604	595
All	956	939	877	877	877

Note: We report the number of firms for different stages of the data preparation process. The numbers shown correspond to July for each year. The "List" column refers to the number of firms for the list which we use to draw time series data. This list is already corrected for static items, which are foreign stocks, non-equities, and additional listings as described in Section 2.1. In addition, we require the dscd code (DSCD), common equity (WC03501), fiscal year end (WC05350) and prices (P) to be non-missing, which are minimum requirements to be included in the portfolio sorts. The "corrected" column refers to the number of firms after the time series screens depicted in Table A.2. The same minimum requirements as for the "list" stocks are also imposed. The "Market", "SMB/HML" and "WML" columns report the number of firms which are actually used to compile the Market Return, the SMB and HML factors and the WML factor. Note that these numbers refer to the value weighted case. In the equal weighted case the numbers would be slightly higher, since the size values of the preceding month are not needed. The "All" row reports the number of unique firms observed over the whole time span.

Table A.8: Number of firms for the Australian market

Year	List	Corrected	Market	SMB/HML	WML
1984	200	175	129		
1985	201	177	132		
1986	214	178	136		
1987	236	191	148	73	133
1988	508	236	169	85	142
1989	681	583	345	122	161
1990	776	593	376	154	327
1991	828	572	384	172	364
1992	936	609	419	170	383
1993	977	611	446	175	421
1994	1,090	687	519	178	446
1995	1,155	713	564	196	509
1996	1,479	1,003	832	235	558
1997	1,561	1,026	883	286	818
1998	1,637	1,041	916	311	850
1999	1,692	1,033	939	351	899
2000	1,850	1,137	1,058	455	919
2001	1,985	1,191	1,137	675	999
2002	2,058	1,171	1,155	1,053	1,090
2003	2,119	1,162	1,147	1,046	1,075
2004	2,260	1,287	1,272	1,097	1,136
2005	2,428	1,394	1,372	1,204	1,204
2006	2,590	1,507	1,483	1,329	1,341
2007	2,821	1,648	1,622	1,415	1,406
2008	3,020	1,743	1,716	1,558	1,503
2009	3,047	1,605	1,589	1,511	1,525
2010	3,117	1,594	1,572	1,464	1,512
2011	3,268	1,653	1,604	1,465	1,486
All	3,393	3,293	2,510	2,494	2,504

Note: We report the number of firms for different stages of the data preparation process. The numbers shown correspond to July for each year. The "List" column refers to the number of firms for the list which we use to draw time series data. This list is already corrected for static items, which are foreign stocks, non-equities, and additional listings as described in Section 2.1. In addition, we require the dscd code (DSCD), common equity (WC03501), fiscal year end (WC05350) and prices (P) to be non-missing, which are minimum requirements to be included in the portfolio sorts. The "corrected" column refers to the number of firms after the time series screens depicted in Table A.2. The same minimum requirements as for the "list" stocks are also imposed. The "Market", "SMB/HML" and "WML" columns report the number of firms which are actually used to compile the Market Return, the SMB and HML factors and the WML factor. Note that these numbers refer to the value weighted case. In the equal weighted case the numbers would be slightly higher, since the size values of the preceding month are not needed. The "All" row reports the number of unique firms observed over the whole time span.

Table A.9: Number of firms for the Canadian market

Year	List	Corrected	Market	SMB/HML	WML
1984	570	463	278		
1985	636	502	296		
1986	721	547	325		
1987	894	671	385	197	322
1988	1,002	845	421	236	382
1989	2,304	1,938	758	243	412
1990	3,307	2,642	1,037	266	749
1991	3,505	2,578	1,080	295	1,020
1992	3,668	2,403	1,131	308	1,070
1993	3,871	2,412	1,205	310	1,137
1994	4,193	2,568	1,321	334	1,196
1995	4,402	2,576	1,390	343	1,311
1996	4,632	2,585	1,477	391	1,374
1997	4,985	2,730	1,596	412	1,455
1998	5,370	2,898	1,737	440	1,572
1999	5,584	2,852	1,800	651	1,703
2000	5,858	2,907	1,902	826	1,763
2001	6,313	3,034	2,039	925	1,838
2002	6,453	2,814	2,056	981	1,971
2003	6,589	2,660	2,099	1,127	2,003
2004	6,799	2,671	2,161	1,167	2,042
2005	7,068	2,730	2,245	1,266	2,093
2006	7,301	2,768	2,334	1,958	2,173
2007	7,512	2,786	2,377	2,051	2,232
2008	7,790	2,783	2,492	2,165	2,240
2009	7,900	2,575	2,417	2,194	2,302
2010	8,023	2,477	2,421	2,159	2,323
2011	8,519	2,729	2,453	2,126	2,300
All	8,765	7,942	3,648	3,596	3,643

Note: We report the number of firms for different stages of the data preparation process. The numbers shown correspond to July for each year. The “List” column refers to the number of firms for the list which we use to draw time series data. This list is already corrected for static items, which are foreign stocks, non-equities, and additional listings as described in Section 2.1. In addition, we require the dscd code (DSCD), common equity (WC03501), fiscal year end (WC05350) and prices (P) to be non-missing, which are minimum requirements to be included in the portfolio sorts. The “corrected” column refers to the number of firms after the time series screens depicted in Table A.2. The same minimum requirements as for the “list” stocks are also imposed. The “Market”, “SMB/HML” and “WML” columns report the number of firms which are actually used to compile the Market Return, the SMB and HML factors and the WML factor. Note that these numbers refer to the value weighted case. In the equal weighted case the numbers would be slightly higher, since the size values of the preceding month are not needed. The “All” row reports the number of unique firms observed over the whole time span.

Table A.10: Portfolio sorts for factor construction

Panel A: Six size-BE/ME portfolios

		BE/ME		
		low	medium	high
size	small	S/L	S/M	S/H
	big	B/L	B/M	B/H

Panel B: Six size-momentum portfolios

		momentum		
		losers	medium	winners
size	small	S/L	S/M	S/W
	big	B/L	B/M	B/W

Note: This table illustrates the sorting procedure which is used to create six size-BE/ME and six size-momentum portfolios which are the building blocks of the SMB, HML and WML factors. Panel A: All stocks are divided into two size groups by their market value (small (S) and big (B)). Simultaneously all stocks are also divided into three BE/ME groups (low (L), medium (M) and high (H)). Panel B: All stocks are divided into two size groups by their market value (small (S) and big (B)). Simultaneously all stocks are also divided into three groups depending on the average returns of the last twelve month, by skipping the most recent one (losers (L), medium (M) and winners (W)). For a discussion of the breakpoints see Section A.2.2 and Table A.11.

Table A.11: Breakpoints for double sorts

	Mean	Median	Minimum	Maximum	Actual
Panel A: Breakpoints for size and BE/ME					
$size_{BP1}$	0.81	0.81	0.76	0.84	0.80
BE/ME_{BP1}	0.35	0.35	0.28	0.42	0.30
BE/ME_{BP2}	0.70	0.70	0.63	0.76	0.70
Panel B: Breakpoints for size and momentum					
$size_{BP2}$	0.81	0.81	0.76	0.86	0.80
mom_{BP1}	0.39	0.40	0.22	0.55	0.30
mom_{BP2}	0.70	0.70	0.54	0.84	0.70

Note: We use the number of portfolio constituents provided by Kenneth French to calculate size and BE/ME breakpoints (Panel A) as well as size and momentum breakpoints (Panel B), which apply to the whole sample (not only to NYSE stocks). We do so to find breakpoints for our sample, which are close to the FF breakpoints. The table shows the size breakpoint ($size_{BP1}$) and the two BE/ME breakpoints (BE/ME_{BP1} and BE/ME_{BP2}) for the building blocks of the SMB and HML factors (Panel A) as well as the size breakpoint ($size_{BP2}$) and the two momentum breakpoints (mom_{BP1} and mom_{BP2}) for the building blocks of the WML factor (Panel B). We report mean, median, minimum and maximum of these empirical FF breakpoints. Furthermore, we report the breakpoints actually employed in this study (column "actual"). The time period ranges from 07/1986 to 02/2012.

Table A.12: Breakpoints for the ten size portfolios by FF

	Mean	Median	Minimum	Maximum	Actual
$size_{BP1}$	0.49	0.49	0.39	0.59	0.45
$size_{BP2}$	0.62	0.62	0.53	0.70	0.60
$size_{BP3}$	0.71	0.71	0.62	0.76	0.70
$size_{BP4}$	0.77	0.77	0.70	0.82	0.75
$size_{BP5}$	0.82	0.82	0.76	0.87	0.80
$size_{BP6}$	0.86	0.87	0.81	0.90	0.85
$size_{BP7}$	0.90	0.90	0.86	0.93	0.90
$size_{BP8}$	0.94	0.94	0.91	0.95	0.93
$size_{BP9}$	0.97	0.97	0.96	0.98	0.96

Note: We use the number of portfolio constituents provided by Kenneth French to calculate size breakpoints, which apply to the whole sample (not only to NYSE stocks). We do so to find breakpoints for our sample, which are close to the FF breakpoints. The table shows the nine size breakpoints ($size_{BP1}$, … , $size_{BP9}$). We report mean, median, minimum and maximum of these empirical FF breakpoints. Furthermore we report the breakpoints actually employed in this study (column "actual"). The time period ranges from 07/1986 to 02/2012.

Table A.13: Breakpoints for the ten BE/ME portfolios by FF

	Mean	Median	Minimum	Maximum	Actual
BE/ME_{BP1}	0.16	0.17	0.10	0.22	0.10
BE/ME_{BP2}	0.26	0.27	0.20	0.33	0.20
BE/ME_{BP3}	0.35	0.35	0.28	0.42	0.30
BE/ME_{BP4}	0.44	0.44	0.36	0.51	0.40
BE/ME_{BP5}	0.53	0.53	0.44	0.60	0.50
BE/ME_{BP6}	0.61	0.61	0.52	0.69	0.60
BE/ME_{BP7}	0.70	0.70	0.63	0.76	0.70
BE/ME_{BP8}	0.79	0.79	0.74	0.84	0.80
BE/ME_{BP9}	0.88	0.88	0.84	0.92	0.90

Note: We use the number of portfolio constituents provided by Kenneth French to calculate BE/ME breakpoints, which apply to the whole sample (not only to NYSE stocks). We do so to find breakpoints for our sample, which are close to the FF breakpoints. The table shows the nine BE/ME breakpoints (BE/ME_{BP1}, … , BE/ME_{BP9}). We report mean, median, minimum and maximum of these empirical FF breakpoints. Furthermore we report the breakpoints actually employed in this study (column "actual"). The time period ranges from 07/1986 to 02/2012.

Table A.14: Breakpoints for the ten momentum portfolios by FF

	Mean	Median	Minimum	Maximum	Actual
mom_{BP1}	0.19	0.19	0.07	0.32	0.10
mom_{BP2}	0.30	0.30	0.14	0.45	0.20
mom_{BP3}	0.39	0.40	0.22	0.55	0.30
mom_{BP4}	0.47	0.48	0.30	0.64	0.40
mom_{BP5}	0.55	0.56	0.38	0.71	0.50
mom_{BP6}	0.63	0.63	0.46	0.77	0.60
mom_{BP7}	0.70	0.70	0.54	0.84	0.70
mom_{BP8}	0.78	0.78	0.62	0.89	0.80
mom_{BP9}	0.86	0.87	0.73	0.94	0.90

Note: We use the number of portfolio constituents provided by Kenneth French to calculate momentum breakpoints, which apply to the whole sample (not only to NYSE stocks). We do so to find breakpoints for our sample, which are close to the FF breakpoints. The table shows the nine momentum breakpoints (mom_{BP1}, … , mom_{BP9}). We report mean, median, minimum and maximum of these empirical FF breakpoints. Furthermore we report the breakpoints actually employed in this study (column "actual"). The time period ranges from 07/1986 to 02/2012.

Table A.15: Breakpoints for the 25 size and BE/ME portfolios of FF

	Mean	Median	Minimum	Maximum	Actual
$size_{BP1}$	0.60	0.60	0.53	0.65	0.60
$size_{BP2}$	0.75	0.75	0.70	0.79	0.70
$size_{BP3}$	0.85	0.85	0.81	0.88	0.80
$size_{BP4}$	0.93	0.93	0.91	0.94	0.90
BE/ME_{BP1}	0.26	0.27	0.20	0.33	0.20
BE/ME_{BP2}	0.44	0.44	0.36	0.51	0.40
BE/ME_{BP3}	0.61	0.61	0.52	0.69	0.60
BE/ME_{BP4}	0.79	0.79	0.74	0.84	0.80

Note: We use the number of portfolio constituents provided by Kenneth French to calculate size and BE/ME breakpoints, which apply to the whole sample (not only to NYSE stocks). We do so to find breakpoints for our sample, which are close to the FF breakpoints. The table shows four size breakpoints ($size_{BP1}$, …, $size_{BP4}$) as well as four BE/ME breakpoints (BE/ME_{BP1}, …, BE/ME_{BP4}). We report mean, median, minimum and maximum of these empirical FF breakpoints. Furthermore we report the breakpoints actually employed in this study (column "actual"). The time period ranges from 07/1986 to 02/2012.

Table A.16: Breakpoints for the 25 size and momentum portfolios of FF

	Mean	Median	Minimum	Maximum	Actual
$size_{BP1}$	0.62	0.62	0.54	0.68	0.60
$size_{BP2}$	0.76	0.76	0.70	0.81	0.70
$size_{BP3}$	0.86	0.86	0.81	0.89	0.80
$size_{BP4}$	0.93	0.93	0.91	0.95	0.90
mom_{BP1}	0.30	0.30	0.14	0.45	0.30
mom_{BP2}	0.47	0.48	0.30	0.64	0.50
mom_{BP3}	0.63	0.63	0.46	0.77	0.60
mom_{BP4}	0.78	0.78	0.62	0.89	0.80

Note: We use the number of portfolio constituents provided by Kenneth French to calculate size and momentum breakpoints, which apply to the whole sample (not only to NYSE stocks). We do so to find breakpoints for our sample, which are close to the FF breakpoints. The table shows four size breakpoints ($size_{BP1}$, …, $size_{BP4}$) as well as four momentum breakpoints (mom_{BP1}, …, mom_{BP4}). We report mean, median, minimum and maximum of these empirical FF breakpoints. Furthermore we report the breakpoints actually employed in this study (column "actual"). The time period ranges from 07/1986 to 02/2012.

Table A.17: One way sorts on size, BE/ME and momentum for the US market

	FF		TR			FF		TR			FF		TR		
	Avg.	σ	Avg.	σ	ρ	Avg.	σ	Avg.	σ	ρ	Avg.	σ	Avg.	σ	ρ
	Size					BE/ME					momentum				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Group 1	0.92	6.29	0.69	6.12	0.94	0.86	5.24	0.78	5.53	0.92	0.23	9.28	-0.21	12.29	0.90
Group 2	0.92	6.58	0.86	5.99	0.93	0.89	4.81	0.84	4.87	0.92	0.79	6.79	0.51	10.08	0.86
Group 3	1.00	6.15	0.96	6.41	0.93	0.96	4.73	0.91	4.85	0.89	0.86	5.72	0.61	8.29	0.84
Group 4	0.91	5.96	0.93	6.24	0.93	0.94	4.94	0.95	4.76	0.91	0.91	4.98	0.67	6.54	0.86
Group 5	0.99	5.86	0.97	6.11	0.93	0.93	4.70	1.01	4.76	0.91	0.83	4.65	0.67	5.77	0.86
Group 6	1.00	5.37	1.00	5.80	0.92	0.87	4.79	0.99	5.00	0.89	0.80	4.53	0.75	4.93	0.88
Group 7	1.05	5.26	1.01	5.56	0.93	1.00	4.57	0.90	5.15	0.84	0.90	4.41	0.89	4.55	0.89
Group 8	1.00	5.27	1.06	5.31	0.93	0.88	4.67	1.08	5.60	0.87	1.02	4.40	0.96	4.59	0.92
Group 9	0.98	4.85	1.01	5.42	0.93	1.02	4.91	1.00	5.83	0.86	0.92	4.81	0.96	5.29	0.87
Group 10	0.83	4.52	0.85	4.64	0.94	1.10	6.15	1.16	6.76	0.82	1.30	6.46	1.43	7.42	0.92
Spread	0.09	4.92	-0.16	5.07	0.87	0.23	4.81	0.38	5.25	0.72	1.06	8.18	1.64	10.79	0.86

Note: We report descriptive statistics for the time series of ten size, BE/ME and momentum groups. We compare two different US datasets with each other: The dataset provided by Kenneth French (FF) and the dataset compiled from TRD and TRW data (TR) as described in Section 2.1. We report the average (Avg.), the standard deviation (σ) and the correlation coefficient between the two datasets (ρ). The time period ranges from 07/1986 to 02/2012.The rows show the ten groups (deciles) of each characteristic, and the spread between the two extreme groups. For Size the spread is group 1 minus group 10, for the other two characteristics it is group 10 minus group 1. All returns are in percent per month and are denominated in US$.

Table A.18: Two way sorts on size-BE/ME and size-momentum for the US market

Panel A: size-BE/ME portfolios

	FF Average					TR Average					ρ				
	L	2	3	4	H	L	2	3	4	H	L	2	3	4	H
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
S	0.24	1.01	1.06	1.22	1.27	0.53	1.03	1.17	1.32	1.29	0.95	0.95	0.94	0.94	0.95
2	0.72	0.96	1.17	1.10	1.08	0.79	0.84	1.04	1.04	1.13	0.93	0.92	0.91	0.90	0.89
3	0.81	1.00	1.06	1.09	1.32	0.71	1.08	1.13	1.16	1.33	0.92	0.91	0.88	0.87	0.85
4	1.04	1.02	0.96	1.12	1.04	0.95	1.01	1.10	1.06	1.42	0.92	0.91	0.90	0.89	0.84
B	0.91	0.95	0.85	0.84	0.90	0.85	0.91	0.96	0.86	0.82	0.94	0.91	0.92	0.85	0.82

Panel B: size-momentum portfolios

	FF Average					TR Average					ρ				
	L	2	3	4	W	L	2	3	4	W	L	2	3	4	W
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
S	0.26	0.82	1.03	1.25	1.57	0.26	0.70	0.98	1.18	1.43	0.95	0.92	0.90	0.92	0.94
2	0.60	0.95	1.08	1.18	1.40	0.34	0.91	1.10	1.15	1.40	0.93	0.90	0.88	0.91	0.91
3	0.76	0.93	1.01	1.03	1.31	0.74	0.96	1.01	1.10	1.30	0.92	0.89	0.90	0.88	0.91
4	0.67	1.03	1.05	1.07	1.21	0.79	1.02	0.97	1.06	1.28	0.93	0.89	0.89	0.87	0.91
B	0.63	0.89	0.77	0.94	1.07	0.54	0.71	0.73	0.93	1.07	0.89	0.90	0.90	0.92	0.91

Note: We report descriptive statistics for the time series of twenty-five size-BE/ME (Panel A) and size-momentum portfolios (Panel B). We compare two different US datasets with each other: The dataset provided by Kenneth French (FF) and the dataset compiled from TRD and TRW data (TR) as described in Section 2.1. We report the average (Average) and the correlation coefficient between the two datasets (ρ). The rows indicate five different size groups for each panel: small (S), second smallest (2), middle (3), second biggest (4) and big (B). The columns for Panel A indicate five different BE/ME groups: low (S), second lowest (2), middle (3), second highest (4) and high (H). The columns for Panel B indicate five different momentum groups: losers (L), second losers (2), middle (3), second winners (4) and winners (W).The time period ranges from 07/1986 to 02/2012. All returns are in percent per month and are denominated in US$.

Table A.19: Simple screens

Panel A: Market returns and common risk factors for the US market – advanced and simple screens

	FF			TR - advanced				TR - simple			
	Avg.	σ	t	Avg.	σ	t	ρ	Avg.	σ	t	ρ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)	(10)	(11)	(12)
VW	0.85	4.67	3.18	0.87	4.77	3.17	0.94	0.86	4.80	3.14	0.94
SMB	0.10	3.32	0.53	0.11	3.14	0.61	0.93	0.08	3.12	0.45	0.93
HML	0.25	3.14	1.40	0.28	3.28	1.50	0.88	0.30	3.35	1.59	0.88
WML	0.53	4.92	1.89	0.64	6.19	1.81	0.93	0.62	7.16	1.51	0.86

Panel B: One way sorts on size, BE/ME and momentum for the US market – simple screens

	FF		TR			FF		TR			FF		TR		
	Avg.	σ	Avg.	σ	ρ	Avg.	σ	Avg.	σ	ρ	Avg.	σ	Avg.	σ	ρ
	size					BE/ME					Momentum				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Group 1	0.92	6.29	0.97	5.98	0.97	0.86	5.24	0.78	5.54	0.92	0.23	9.28	0.12	19.77	0.59
Group 2	0.92	6.58	1.12	6.58	0.93	0.89	4.81	0.85	4.88	0.92	0.79	6.79	-0.06	11.17	0.83
Group 3	1.00	6.15	0.93	6.06	0.93	0.96	4.73	0.89	4.85	0.89	0.86	5.72	0.62	8.90	0.83
Group 4	0.91	5.96	1.04	5.95	0.93	0.94	4.94	0.94	4.76	0.91	0.91	4.98	0.58	7.22	0.84
Group 5	0.99	5.86	1.00	5.74	0.92	0.93	4.70	1.01	4.86	0.90	0.83	4.65	0.73	6.16	0.83
Group 6	1.00	5.37	0.96	5.57	0.92	0.87	4.79	0.98	5.02	0.89	0.80	4.53	0.73	5.18	0.87
Group 7	1.05	5.26	1.09	5.24	0.93	1.00	4.57	0.91	5.18	0.84	0.90	4.41	0.86	4.72	0.87
Group 8	1.00	5.27	0.99	5.41	0.93	0.88	4.67	1.10	5.73	0.87	1.03	4.40	0.98	4.46	0.92
Group 9	0.98	4.85	1.01	5.33	0.93	1.02	4.91	1.01	5.90	0.86	0.92	4.81	0.98	5.08	0.89
Group 10	0.83	4.52	0.85	4.64	0.93	1.10	6.15	1.15	6.87	0.83	1.30	6.46	1.38	7.25	0.93

Note: Panel A of this table reports descriptive statistics for the time series of monthly value weighted (VW) market returns as well as the returns of the SMB, HML and WML factors in %. We compare three different US datasets with each other: The FF and two versions of TRD and TRW (TR) as described in Section 2.2.3. In Panel B, we report descriptive statistics for the time series of ten size, BE/ME and momentum groups. We compare two different US datasets with each other: The dataset provided by Kenneth French (FF) and the dataset compiled from Thomson Reuters Datastream and Thomson Reuters Worldscope data (TR) as described in Section 2.1. We report the average (Avg.), the standard deviation (σ), the t-statistic (t) and the correlation coefficient between the two datasets (ρ). The t-statistic refers to the null hypothesis that the mean of the tested series is zero. The time period ranges from 07/1986 to 02/2012. All returns are in percent per month and are denominated in US$.

Table A.20: Drawing dates

Country	Start - 1st draw	End - 1st draw	Start - 2nd draw	End - 2nd draw
Australia	Jan-80	Dec-10	Dec-10	Mar-13
Austria	Jan-80	Oct-09	Apr-09	Jul-12
Belgium	Jan-80	Nov-09	Apr-09	Jul-12
Canada	Jan-80	Mar-11	Mar-11	Apr-13
Czech Republic	Jan-80	Dec-09	Apr-09	Jul-12
Denmark	Jan-80	Nov-09	Apr-09	Jul-12
Finland	Jan-80	Dec-09	Apr-09	Jul-12
France	Jan-80	Nov-09	Apr-09	Jul-12
Germany	Jan-80	Nov-09	Apr-09	Jul-12
Greece	Jan-80	Nov-09	Apr-09	Jul-12
Hong Kong	Jan-80	Dec-11	Dec-11	Mar-13
Hungary	Jan-80	Dec-09	Apr-09	Jul-12
Ireland	Jan-80	Nov-09	Apr-09	Jul-12
Italy	Jan-80	Nov-09	Apr-09	Jul-12
Japan	Jan-80	Dec-09	Dec-09	Nov-12
Luxembourg	Jan-80	Nov-09	Apr-09	Jul-12
Netherlands	Jan-80	Nov-09	Apr-09	Jul-12
Norway	Jan-80	Nov-09	Apr-09	Jul-12
Poland	Jan-80	Dec-09	Apr-09	Jul-12
Portugal	Jan-80	Nov-09	Apr-09	Jul-12
Singapore	Jan-80	Dec-11	Dec-11	Mar-13
Slovakia	Jan-80	Dec-09	Apr-09	Jul-12
Spain	Jan-80	Nov-09	Apr-09	Jul-12
Sweden	Jan-80	Jul-11	Apr-09	Jul-12
Switzerland	Jan-80	Oct-09	Apr-09	Jul-12
Turkey	Jan-80	Nov-09	Apr-09	Jul-12
UK	Jan-80	Nov-09	Apr-09	Jul-12
USA	Jan-80	Apr-09	Apr-09	Mar-12

Note: This Table shows the time spans applied to the first and second drawing procedure for each country.

Table A.21: Overview: risk free rate proxy composition

Country	Riskfree rate proxy	Horizon	Euro OIS	Series used	Description of Series used
Australia	TBill	3 month		ADBR090	AUSTRALIA DEALER BILL 90 D - MIDDLE RATE
Austria	IBR + OIS	3 month	Yes	OEINTER3, OIEUR3M	OE INTERBANK OFFERED RATE: THREE MONTH, EURO 3 MONTH OIS - MIDDLE RATE
Belgium	TBill	3 month		BGTBL3M	BELGIUM TREASURY BILL 3 MONTH - MIDDLE RATE
Canada	TBill	3 month		CNTBL3M	CANADA TREASURY BILL 3 MONTH - MIDDLE RATE
Denmark	IBR + OIS	3 month	No	CIBOR3M, OIDKK3M	DENMARK INTERBANK 3 MONTH - OFFERED RATE, DANISH KRONE 3 MONTH OIS - MIDDLE RATE
Finland	IBR + OIS	3 month	Yes	FNIBF3M, OIEUR3M	FINLAND INTERBANK FIXING 3 MONTH - OFFERED RATE, EURO 3 MONTH OIS - MIDDLE RATE
France	TBill	3 month		FRTBL3M	FRANCE TREASURY BILL 3 MONTHS - BID RATE
Germany	IBR + OIS	3 month	Yes	FIBOR3M, OIEUR3M	GERMANY INTERBANK 3 MONTH - OFFERED RATE, EURO 3 MONTH OIS - MIDDLE RATE
Greece	TBill	3 month		GDTBL3M	GREECE TREASURY BILL 3 MONT - MIDDLE RATE
Hong Kong	TBill	3 month		HKGBILL3	HK TREASURY BILL RATE - 3 MONTH
Ireland	IBR + OIS	3 month	Yes	IRINTER3, OIEUR3M	IRELAND INTERBANK 3 MONTH - OFFERED RATE, EURO 3 MONTH OIS - MIDDLE RATE
Italy	TBill	3 month		ITBT03G	ITALY T-BILL AUCT. GROSS 3 MONTH - MIDDLE RATE

Japan	TBill			ST'STRECLUCON	Short term Money Market Rate/Call Rates - Call Rates, Uncollateralized Overnight/End of Month
Netherlands	IBR + OIS	3 month	Yes	HOLIB3M, OIEUR3M	NETHERLAND INTERBANK 3 MTH - MIDDLE RATE, EURO 3 MONTH OIS - MIDDLE RATE
Norway	TBill + IBR	3 month		NWIBK3M, NWTBL3M	NORWAY INTERBANK 3 MONTH - OFFERED RATE, NORWAY T BILL 3 MONTH - RED. YIELD
Poland	IBR + OIS	3 month	No	POIBK3M, OIPLN3M	POLAND INTERBANK 3 MONTH (EOD) - MIDDLE RATE, POLISH ZLOTY 3 MONTH OIS - MIDDLE RATE
Singapore	TBill	3 month		SNGTB3M	SINGAPORE T-BILL 3 MONTH - MIDDLE RATE
Spain	TBill	1-3 month		ESTBL3M	SPAIN TREASURY BILL 1-3 MONTH - RED. YIELD
Sweden	TBill	3 month		SDTB90D	SWEDEN TREASURY BILL 90 DAY - MIDDLE RATE
Switzerland	IBR + OIS	3 month	No	SWIBK3M, OICHF3M	SWISS INTERBANK 3M (ZRC:SNB) - BID RATE, SWISS FRANC 3 MONTH OIS - MIDDLE RATE
Turkey	IBR	3 month		TKIBK3M	TURKISH INTERBANK 3 MONTH - MIDDLE RATE
UK	TBill	3 month		UKTBTND	UK TREASURY BILL TENDER 3M - MIDDLE RATE
USA	TBill	3 month		USGBILL3	US TREASURY BILL RATE - 3 MONTH (EP)

Note: This Table shows how the riskfree rate proxies for each country are composed. The following abbreviations are used: Treasury bill – TBill, interbank rate – IBR, overnight indexed swap - OIS. Source: Thomson Reuters Datastream and Bank of Japan.

Table A.22: Countries ranked on market capitalization

Rank	Country	Market Cap.
1	USA	16,542,094.86
2	Japan	3,808,949.09
3	UK	3,024,832.69
4	France	2,077,363.46
5	Canada	2,007,672.50
6	Germany	1,550,456.99
7	Hong Kong	1,443,260.99
8	Australia	1,392,976.77
9	Switzerland	1,214,195.38
10	Spain	737,219.13
11	Italy	602,712.22
12	Netherlands	573,542.31
13	Sweden	542,530.63
14	Singapore	502,068.55
15	Norway	299,763.18
16	Turkey	283,428.33
17	Belgium	251,438.96
18	Poland	205,636.70
19	Denmark	205,435.71
20	Finland	196,656.16
21	Austria	131,247.48
22	Portugal	76,344.76
23	Greece	61,983.68
24	Czech Republic	52,548.52
25	Ireland	50,565.03
26	Luxembourg	34,537.19
27	Hungary	32,574.75
28	Slovakia	3,955.27
29	Iceland	1,827.67

Note: The table shows all countries used in this study ranked by their total market capitalization (Market Cap.) in million US$ in June 2011. The data are from TRD.

Table A.23: Turnover and trading volume of the smallest and biggest of the ten size portfolios

	Portfolio turnover				Trading volume			
	NYSE BPs		Equal BPs		NYSE BPs		Equal BPs	
	Pf 1	Pf 10	Pf 1	Pf 10	Pf 1	Pf 10	Pf 1	Pf 10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Australia	7.09	1.47	11.74	1.37	304.74	28,310.92	49.92	34,197.08
Canada	8.13	1.44	13.44	1.25	483.42	32,110.98	18.72	43,575.67
Denmark	3.97	1.68	5.75	1.49	45.48	3,179.26	3.07	4,473.90
France	4.72	1.86	7.87	1.31	131.35	55,014.83	4.44	72,970.66
Germany	6.26	1.58	39.45	1.41				
Hong Kong	7.73	2.69	12.72	2.43	428.5	8,917.03	106.47	29,195.58
Italy	5.54	2.36	17.74	2.04	533.27	38,896.06	66.23	49,816.60
Japan	4.2	1.55	6.80	1.38	3,467.79	113,908.70	264.26	157,485.00
Netherlands	3.87	1.84	8.02	1.34	276.8	24,577.50	27.47	36,685.43
Norway	6.07	2.3	10.69	2.23	170.57	7,075.59	10.42	9,789.20
Singapore	5.83	2.57	9.22	2.27	273.82	4,272.36	33.02	6,874.35
Switzerland	4.26	1.43	6.95	1.22	226.56	29,822.64	7.92	36,875.18
UK	6.49	1.29	9.91	1.14	487.85	115,117.69	29.69	145,822.18
US	7.47	1.48	22.70	1.31	6,529.10	1,127,264.01	440.78	1,443,648.06
Average	5.83	1.82	13.07	1.59	1,027.63	122,189.81	81.72	159,339.15

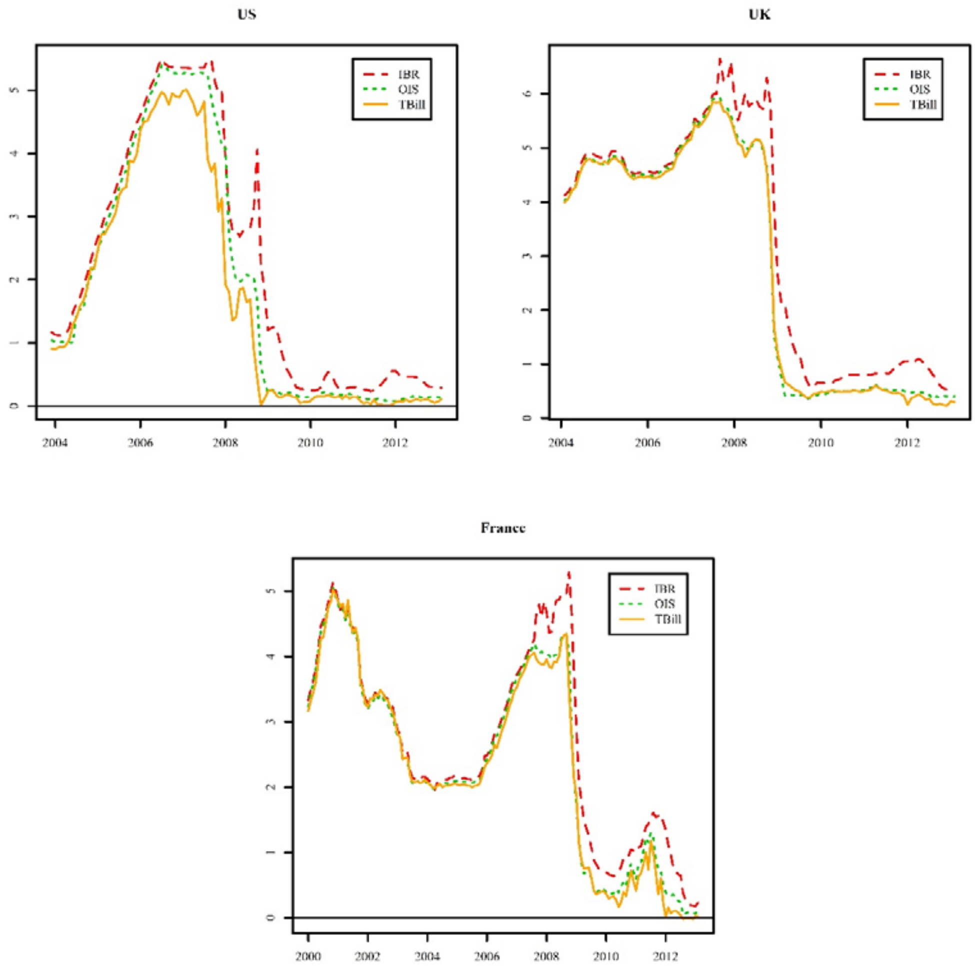
Note: We report the average turnover and average trading volume of the smallest (Pf 1) and biggest portfolios (Pf 10) involved in the size strategies examined. We calculate turnover based on a value weighted scheme, according to the corresponding portfolios. We calculate trading volume by multiplying the TRD variable ‘turnover by volume’ (VO) with the ‘adjusted price’ (P) on a monthly basis. Turnover as well as trading volume is reported for the all months of the sample. Turnover is reported in per cent and on a monthly basis. Trading volume is reported in million US$ on a monthly basis. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Japan, Singapore, Switzerland, UK, US; 07/2001-02/2012: Hong Kong; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table A.24: Turnover and trading volume of the smallest and biggest of the five size portfolios

	Portfolio turnover		Trading volume	
	Pf 1	Pf 5	Pf 1	Pf 5
	(1)	(2)	(3)	(4)
Australia	9.87	1.27	23.43	38,086.60
Austria	5.91	2.05	4.71	2,259.81
Belgium	5.04	1.23	3.66	5,802.11
Canada	10.73	1.15	57.36	46,508.91
Denmark	5.36	1.22	9.12	5,192.85
Finland	5.91	1.47	7.50	12,184.00
France	6.49	1.22	39.48	76,508.78
Germany	14.60	1.29		
Greece	7.35	1.96	119.97	2,975.70
Hong Kong	10.51	2.38	234.48	31,937.86
Ireland	8.58	1.31	3.52	2,825.45
Italy	9.55	1.74	156.59	55,471.21
Japan	5.62	1.28	736.14	177,540.59
Netherlands	6.28	1.22	49.39	41,772.21
Norway	8.52	2.01	35.52	10,951.77
Poland	7.73	4.08	57.47	1,950.65
Singapore	7.58	1.93	76.75	7,170.35
Spain	6.72	1.33	105.25	35,761.40
Sweden	8.63	1.41	33.12	23,305.04
Switzerland	5.37	1.17	29.87	39,988.10
Turkey	9.03	3.62	604.20	16,831.13
UK	10.94	1.09	96.63	156,606.13
US	13.07	1.22	1,050.47	1,613,099.62
Average	8.23	1.68	160.67	109,305.92

Note: We report the average turnover and average trading volume of the smallest (Pf 1) and biggest portfolios (Pf 5) involved in the size strategies examined. We calculate turnover based on a value weighted scheme, according to the corresponding portfolios. We calculate trading volume by multiplying the TRD variable 'turnover by volume' (VO) with the 'adjusted price' (P) on a monthly basis. Turnover as well as trading volume is reported for the all months of the sample. Turnover is reported in per cent and on a monthly basis. Trading volume is reported in million US$ on a monthly basis. We use the following time periods: 07/1991-02/2012: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Singapore, Spain, Sweden, Switzerland, UK, US; 01/2001-02/2012: Hong Kong; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway; 01/1996-02/2012: Poland; 07/2006-02/2012: Turkey.

Figure A.1: Treasury bills, overnight indexed swaps and interbank rates for US, UK and France



Note: This Figure shows 3 month treasury bills (TBill), overnight indexed swaps (OIS) and interbank rates (IBR) for US, UK and France. Source: TRD.