On the Construction of Common Size, Value and Momentum Factors in International Stock Markets: A Guide with Applications

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Abstract

A major obstacle for research in international asset pricing and corporate finance has been a lack of reliable and publicly available data on international common risk factors and portfolios. To address this gap, we provide a step-by-step description of how appropriately screened data from Thomson Reuters Datastream and Thomson Reuters Worldscope can be used to construct high-quality systematic risk factors. We provide common risk factors for 23 countries across the globe. To demonstrate the use of this dataset, we present evidence of an "extreme" size premium in a large number of countries. These premia, however, are most likely not realizable due to a low stock market depth.

JEL classification: C89, G12, G15

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1. Introduction

Many path-breaking results in empirical finance have been established for U.S. data by the investigation of the well-known Center for Research in Security Prices (CRSP) and COMPUSTAT datasets. Very prominently, the empirical failure of the one-factor model based on the Capital Asset Pricing Model (CAPM) has been documented using these data. For example, Fama and French (1993) show that their three-factor model – consisting of the market, value, and size risk factors – explains the cross-section of stock returns better than the one-factor model. Although there is an ongoing discussion of what the economic mechanism is by which passive investing in value firms and those with a relatively small market capitalization earns high expected returns, it has become common to control for these three factors in a wide range of applications. Moreover, Jegadeesh and Titman (1993) show for the U.S. 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.

Researchers and practitioners alike are increasingly eager to determine the existence or non-existence of these anomalies in markets outside of the U.S. as well. Sometimes, a specific market per se is interesting; moreover, some factors may be more important in some countries than in others due to specific characteristics of individual markets. In addition to allowing the study of anomalies in different contexts (thus providing tests for theories that have been developed to explain anomalies in the U.S.), international data can address a common objection that anomalies observed in the U.S. market may possibly be a manifestation of survivorship or data-snooping biases (Kothari et al., 1995; Lo and MacKinlay, 1990; MacKinlay, 1995). Moreover, to implement standard applications in empirical finance such as long-run event studies or portfolio analyses also in non-U.S. markets, the researcher requires reliable risk-adjusted returns based on an asset pricing model. In sum, there is a considerable need in the research community for high-quality data and reliable risk factors in international markets.

This guide addresses this need. 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 U.S. 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.

In constructing the dataset, 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.[1,2]

We use TRD (which mainly covers stock market data such as prices and dividends) and TRW data (which mainly covers accounting data such as common equity). It is well-known that data from TRD

[1] 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), TRD (U.K. and Canada) and CRSP/COMPUSTAT (U.S.). 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-U.S. 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 risk factors are not available to other researchers, though there are also important exceptions. Fama and French (2012) and Asness and Frazzini (2013) provide their international risk factor data as well. We compare our data with Fama and French (2012) where it overlaps.

[2] Since the circulation of the first version of this paper 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. By May 21, 2016, according to Google Scholar, 54 papers are using either our risk factor dataset (EXAMPLE: Avramov et al. 2012), or are following our recommendations in constructing their own data according to their specific needs.

can be prone to errors. For example, Ince and Porter (2006) show that the momentum effect is not detectable by using these raw data for the U.S. To circumvent these problems, Ince and Porter (2006) suggest some corrections that allow them to obtain similar results for momentum in the TRD dataset. In this paper, we build upon their screens and further expand them.

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 U.S., 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).[3] 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 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.

We also present novel evidence on the size effect. Since the discovery of the so-called size effect by Banz (1981) this issue has been controversially discussed.[4] 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; Schwert, 2003, for the U.S.). 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.

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[4] For a recent overview of the topic see, for example, van Dijk (2011).

Our main results on the profitability of size is 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 for a pooled international dataset that the smallest 10% of the firms earn a significant premium over the biggest 10 % firms. Our study 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. We find that size premiums, even where they exist, are most likely not realizable because the U.S. dollar trading volumes of the involved portfolios are rather small.

The paper proceeds as follows. We first explain, in Section 2, the data preparation and the general construction of the risk factors (Section 2.1). Then, we compare our novel market returns and risk factors with other data sources (Sections 2.2 and 2.3). In Section 3 we present the empirical results for the size premium. Section 4 concludes.

2. Data

Section 2.1 describes briefly the data preperation 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 U.S. market returns and common risk factors from our dataset with the corresponding series from Kenneth French's website (Sections 2.2.1 and 2.2.2). In addition, we investigate the quality of our dataset by comparing single and double sorted portfolio groups on various characteristics from Kenneth French's dataset with ours (Section 2.2.3). Section 2.3 conducts checks for the non-U.S. markets. We compare self-created local market indices with publicly available local market indices. (Section 2.3.1). 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 (Sections 2.3.2 and 2.3.3).

2.1. Data preparation and common risk factors

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 improves over time. Therefore, in a sample 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 U.S. and a time period from 1991 to 2012 for most of the other countries (coverage for some countries is too limited before 1989).[5] 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, 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.[6] The dynamic screens remove constant prices at the end of the

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

[6] Using the equity type in TRD (EQ) should generally correspond to sharecodes 10 and 11 in CRSP. However, this correspondence is far from perfect, therefore we conduct additional screens to ensure that the selected stocks are common equity. For details on this issue see Ince and Porter (2006, p. 466; 471).

sample 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 sample 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.

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 section A.2 of the Appendix. 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 U.S. stock market

2.2.1. Market returns and common risk factors

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 U.S. 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 using TRD data. The correlation coefficient between the two value weighted returns is 0.94.

[Table 1 here]

We now analyze the time series of the U.S. SMB, HML, and WML factors.[7] The corresponding results are also shown in Table 1. The average values for the SMB factors are rather low and amount to 0.10% per month (FF data) and 0.11% (TRD and TRW data). The correlation coefficient between the two SMB factors based on the FF and our TRD and TRW dataset 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 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 (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. In addition, we show in appendix A.2.3 that test portfolios, sorted on single characteristics as well as joint sorts on two characteristics are similar to the Kenneth French versions.

2.2.2. Are the detailed screens necessary?

Another important question is whether the advanced screens applied in this paper are really necessary or if simpler ones perform just as well. To answer this question, we apply a very simple screening procedure and just eliminate returns above 300% as well as the outliers as indicated in footnote 33 in Appendix A.1. 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. The results for the U.S. factors are shown in Table 2. The market portfolio as well as the SMB and HML

[7] We explain the construction of theses factors in section A.2.1 in detail.

factors of the simple screens are remarkably close to the FF versions and the versions of 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 at the 10% significance level.

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 2 here]

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 3 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).[8]

[Table 3 here]

There are differences by construction between the publicly available local indexes, which we use for comparison, and the self-compiled 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 information.[9] 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.[10] 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 (U.S.)) 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

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[8] 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 U.S. 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 3.

[9] For example, the U.S. value weighted market returns on CRSP 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.

[10] 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), U.S. (both periods), Luxembourg (second period), Greece (both periods), Hungary (MSCI) and Czech Republic (both periods). All other indices are pure price indices.

results for countries for which we use different time periods, due to data availability restrictions.[11]

The main result of this analysis is that for the twenty-five biggest international stock markets[12] 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 (U.S., 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), and Iceland (data are only available for the 01/2001 – 06/2012 period).[13]

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 4 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

[11] 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).

[12] 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.

[13] We suspect that the relatively 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.

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 U.S. data.

For the Japanese dataset as shown in Panel B of Table 4 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 is high, amounting to 0.94.

[Table 4 here]

We next compile overall common risk factors. The results are also shown in Table 4. 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 U.S. 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 U.S., but also quite high, amounting to 0.91.

For Japan, the average SMB and HML returns are a bit more dispersed than for the U.S. and European samples, 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. 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 U.S.

3. Application: Size effect

This section presents an analysis of the much debated size effect as an application of the data discussed in the previous section.

3.1. International size premiums

We consider two different approaches to detect a possible size effect: First, we calculate the SMB factor based on approximate NYSE breakpoints as described in detail in Appendix A.2.2. 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 5 display the results.[14] A positive mean return of the SMB factor is obtained for seven of the 14 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.

[14] 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.

[Table 5 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 portfolio 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 estimated by considering the intercepts of a regression of the spread portfolio (the "1-10-spread") on the market, SMB, HML, and WML factors:

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

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 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 5. Nine out of 14 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 8. As expected, correcting for the risk factors lowers the estimated size premiums and also the t-statistics. Here, ten out of 14 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 5 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 6, are greater than zero for all countries examined and different from zero at the 10% significance level for nine out of 14 countries.

[Table 6 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 U.S. 1-10 spread of 1.46% in our country dataset, which is plausible given that U.S. data probably have a significant influence on the aggregate international dataset.[15] Besides focusing on individual countries, another difference between our studies is that we use value weighted returns, whereas De Moor and Sercu (2013) use equal weighted returns.[16]

[15] Our study (and the one by De Moor and Sercu (2013)) uses equal breakpoints for the creation of the 1-10 spread portfolio.
[16] 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

Third, we wish to consider a larger number of countries.[17] Therefore, we construct quintile instead of decile portfolios.[18] This approach allows us to examine nine additional countries. The results for the raw returns are shown in columns (7) and (8) of Table 5. 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 6 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 14 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 23 countries 21 estimated size premiums are positive and ten of them are significant (10% level).

In sum, 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 U.S., France, or Canada also show huge returns with 1.45%, 1.30%, and

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may amplify model problems. Novy-Marx and Velikov (2016) 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. 106).

[17] 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 periods. 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.

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

3.08% (19%, 17%, and 44% annualy). By way of comparison, the market excess return for the U.S. 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 U.S. 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 U.S. 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.[19] 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. For example, 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. We address the question of practical implementability explicitly in Section 3.2.

[19] See Table A.12.

3.2. International size premiums when adjusting for trading costs

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

3.2.1 Trading costs and trading volume

To account for actual implementability of the strategies discussed in section 3.1, we apply three different, but complementary approaches. The first one assumes fix trading costs per trade and utilizes turnover data to calculate trading costs for each portfolio. 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). A detailed treatment of these approaches is given in Schmidt et al. (2017).

Our first approach assumes a fixed amount of costs per trade, thereby utilizing portfolio turnover data. Note that, while one the one hand we make here a big assumption, we also do, on the other hand utilze data which are crucial for trading costs, namely portfolio turnover. We thereby 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. These values are taken from Frazzini et al. (2012).

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.

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:[20]

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

where T is the number of periods, t_{crit} is the critical value of the assumed t-test, 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 U.S. 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 U.S. 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 U.S. dollars. Using the last price of each month and multiplying it by all traded shares of the whole month is an approximation.

[20] Note that this is an approximate formula. The correct formula as well as the derivation of the approximate formula are disscussed in Schmidt et al. (2017). Using this approximation does not change the results qualitatively.

3.2.2 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.[21]

3.2.3 Critical trading costs

Table 7 shows critical trading costs as described in Section 3.2.1. We only report positve values since negative values have no meaning in this context. Thus, naturally, for the SMB return the critical trading 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 U.S., 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 U.S. the countries with notable critical trading costs are the same. For the newly added countries, Greece has the highest critical trading

[21] At first sight higher estimated alphas and t-statistics after a correction for tradings costs appears to be counterintuitive. The reason for this result is that we correct the test portfolios as well as the factors, so that the factor sensitivities might also change, leading to this outcome. However, the differences to the results without trading costs are rather small.

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.

[Table 7 here]

3.2.4 Trading volume and market depth

In Tables 8 and 9 we report the average portfolio turnover of the long and short portfolio of the 1-10 and 1-5 spreads, respectively. As before, we provide versions with NYSE and equal breakpoints. Moreover, we chose to report the portfolio turnover of July, when the portfolio is yearly rebalanced.[22]

The average portfolio turnover values in July of the small (big) portfolio in the 1-10 spread with NYSE breakpoints are about 60% (15%) on average. For the case with equal breakpoints the turnover values for the big portfolio are slightly lower (about 10%) and considerably higher for the small portfolios with about 130%.[23] 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.

[22] Note that July values are effectively the yearly turnover values, since the portfolio is rearranged every July. Therefore, Tables 8 and 9 use only July values. Yearly values are not reported, but are available on request.
[23] The corresponding numbers for the 1-5 spread in Table 9 are between those two extreme cases.

[Table 8 here]

[Table 9 here]

Tables 8 and 9 also report average U.S. dollar trading volumes of the 1-10 and 1-5 spread strategies, respectively. The average U.S. dollar trading volumes for the small size portfolio with NYSE breakpoints range from U.S.$38 million for Denmark to U.S.$3,815 million for the U.S., in July (see column 5). The average U.S. dollar trading volumes for the big size portfolio with NYSE breakpoints are much bigger and range from U.S.$3 billion in Denmark to U.S.$1,090 billion in the U.S. (column 6). Therefore, the average U.S. dollar trading volume of the big size portfolio is for all countries at least ten times as high as for the small portfolio and often hundred times as high or even higher.

We now turn to the results with equal breakpoints for July, reported in columns (7) and (8) of Table 8. The average U.S. dollar trading volumes of the small size portfolios are now much smaller, ranging from below U.S.$2 million to U.S.$376 million. The average trading volume of the big size portfolio is, therefore, slightly higher, ranging from U.S.$4 billion (Denmark) to U.S.$1,400 billion (U.S.). The average U.S. dollar trading volumes for the small quintile portfolios, shown in column (3) of Table 9 are higher, but still not impressive, ranging from U.S.$3 million (Ireland) to U.S.$805 million (U.S.). For the big quintile portfolio, in column (4), these values range from U.S.$2 billion (Poland) to U.S.$1,600 billion (U.S.).

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 U.S.$1.5 billion and U.S.$15 billion for the U.S.. We assume that a fund should have at least a size of U.S.$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 8. Consider first the case of the size portfolios with NYSE breakpoints from Table 8. For the U.S., for example, the avarage monthly turnover in July of the small size portfolio is 74% (Table 8, column (1), second last row). If we assume that we invest in all available small size stocks in the U.S. (with the proportions according to our value weights) we trade stocks with a volume of U.S.$3.8 billion each July on average (Table 8, column (5), second last row). Thus, we can conclude that the average maximum fund size (the 100%) is U.S.$3.8 billion / 0.74 ≈ U.S.$5 billion. Assuming that the hypothetical fund of U.S.$1.5 billion is equally divided between small and big stocks, we end up with a small size portfolio of about U.S.$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. (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 U.S.$250 million for the U.S.[24] This is less than the U.S.$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 U.S.$500 million (which is double the U.S.$250 million, since the long position is assumed to be the same amount) for the U.S.. If we do so, however, we would have a very high price impact and trading costs will rise by a large amount.[25] The same problem occurs

[24] The avarage monthly turnover in July of the small size portfolio in the US is 154% (Table 8, column (3), second 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 8, column (7), second 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.

[25] 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).

for the 1-5 spread where the maximum fund size is about U.S.$700 million for the U.S. 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 U.S. However, the cumulated maximum fund sizes for the other countries are at best about 2.5 times as much as for the U.S. (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 U.S. are 1.45% - 1.41% = 0.04 % which are about 0.48% on a yearly basis.

3.2.5 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 strategies are actually realizable since the U.S. dollar trading volumes 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 volumes 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. Conclusion

A major obstacle for research in international asset pricing and corporate finance has been a lack of reliable and publicly available data on international common risk factors and portfolios. With this guide, we aim to make a step towards overcoming this obstacle. Specifically, this paper provides a detailed analysis of how to construct high-quality, replicable portfolios and common risk factors from Thomson Reuters Datastream (TRD) and Thomson Reuters Worldscope (TRW) data.

We first outline appropriate screens and data filters by which the quality and the reliability of the data can be raised significantly. This is demonstrated for the U.S., for which we show that the discussed data screening procedures lead to portfolios and common risk factors based on TRD and TRW data that have very similar properties as those obtained from CRSP and Compustat. Furthermore, we expand the analysis to international stock markets, showing that the correlations of our self-compiled value weighted indices with well-known representative stock market indices are very high.

Moreover, we show that an extreme size premium exists in several individual countries. When accounting for trading costs, we find that all size premiums are probably not realizable because the U.S. dollar trading volumes of the small size stocks needed for implementation are too low and actually trading these stocks with appropriate quantities would presumably increase stock prices and decrease the profitability of these strategies significantly.

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Table 1: Market returns and common risk factors for the U.S. 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. We compare two different U.S. 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 U.S.$.

Table 2: Market returns and common risk factors for the U.S. 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

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. We compare three different U.S. datasets with each other: The FF and two versions of TRD and TRW (TR) as described in Section 2.2.2. 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 U.S.$.

Table 3: 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	0.83	2.18	0.99	0.77	0.63	0.71	1.94	0.99	0.80
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 3 (continued): Comparison with international 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 to 06/2012 and a short one, typically ranging from 07/1999 to 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, U.S.), 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 4: 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)
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 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 U.S.$.

Table 5: Size returns – univariate sorts

	SMB		1-10 (NYSE BPs)		1-10 (Equal BPs)		1-5 (Equal BPs)	
	Mean	t	Mean	t	Mean	t	Mean	t
	(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	0.10	0.51	1.30	3.45	3.08	5.14	2.09	4.48
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	1.30	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
U.S.	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-statistics. 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). 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-statistics. t-statistics refer to the null that the means are equal to zero. Mean returns are in percent per month and are denominated in U.S.$. 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, U.S.; 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: 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	0.79	2.80	2.56	4.70	1.61	3.97	1.07	3.23
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
U.S.	-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: $(r_t^s - r_t^b) = \alpha + \beta_M * (r_{M,t} - r_{f,t}) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{WML} * WML_t + \varepsilon_t$ 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-statistics 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-statistics 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. t-statistics refer to the null that the alphas are zero. Mean returns are in percent per month and are denominated in U.S.$. 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, U.S.; 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 7: 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	1041.87	860.20	1470.94	1326.63	1389.47	1235.52
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
U.S.	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} as 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 in small stocks and short in big stocks, we already subtract 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 positive critical 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, U.S.; 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 8: 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	68.66	14.48	102.30	10.51	700.17	26,697.25	34.47	38,505.20
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
U.S.	74.19	11.49	153.94	9.39	3,814.54	1,088,994.16	375.85	1,406,860.74
Average	58.63	14.67	129.47	11.91	814.10	119,717.16	60.45	156,982.02

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 are reported for the July values of the dataset. Turnover is reported in percent and on a monthly basis. Trading volume is reported in million U.S.$ on a monthly basis. We use the following time periods: 07/1991-02/2012: Australia, Canada, Denmark, France, Germany, Italy, Japan, Singapore, Switzerland, UK, U.S.; 07/2001-02/2012: Hong Kong; 07/1991-06/2011: Netherlands; 07/1993-02/2012: Norway.

Table 9: 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	91.10	9.35	110.34	43,454.20
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
U.S.	116.33	8.31	805.15	1,578,656.99
Average	82.34	12.83	133.19	106,179.10

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 percent and on a monthly basis. Trading volume is reported in million U.S.$ 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, U.S.; 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.

A. Supplementary Appendix

A.1. Data preparation

Like Ince and Porter (2006, p. 465), we use Thomson Reuters Datastream (TRD) constituent lists to construct our dataset. Besides research lists, we also use dead lists, Thomson Reuters Worldscope (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.[26] 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.[27] The lists are provided in sections A.1.1 (U.S.) and A.1.2 (International).

On the basis of this initial sample (53,517 unique U.S. firms and 43,376 unique European firms),[28] 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 U.S. 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,

[26] Ulbricht and Weiner (2005, p. 12-16, fig. 2-4) find a difference in the firm size structures between the TRW and COMPUSTAT databases which "diminishes over the years and is virtually not noticeable after 2002". Since TRW 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).

[27] 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 TRD and TRW.

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

ADRs, etc.) or simply no data are available. See also Table A.1 for an overview of theses static screens (SS01-SS03). We also use some additional static filters (SS04 and SS05). We include stocks listed on all domestic exchanges, with the exception of Canada, where we exclude stocks listed on the TSX Venture exchange.[29]

[Table A.1 here]

After these static screens, 32,585 firms remain for the U.S. and 23,709 for Europe.[30] 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).[31]

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.[32]

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[29] Carpentier et al. (2010) describe the TSX Venture Exchange as a direct competitor for conventional venture capital. Brander et al. (2010, p. 289) describe a listing on the TSX Venture Exchange as "… a less impressive exit event than a listing on the TSE, New York Stock Exchange (NYSE), or National Association of Securities Dealers Automated Quotations (NASDAQ)". We therefore view these stocks also as a somehow different asset as most of the other stocks in the sample, and consequently exclude them.

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

[31] Occasionally, the fiscal year entry (such as "12/1999") is missing, but at least one item of the actual TRW 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).

[32] 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).

[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 U.S. 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) U.S. (European) firms pass the time series screens described in Table A.2. In the end we use 15,239 (11,315) U.S. (European) firms to construct the value weighted market factor, 14,129 (11,239) firms to construct the SMB and HML factors and 15,238 (11,310) firms to construct the WML factor. All numbers are for unique firms over the whole time span.

The U.S. 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,[33] 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

[33] Since most exchange rate series available on TRD 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.

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 U.S. sample. We note that this implies that our U.S. 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 U.S. 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 conversion rate and express all cash values (like size) in euro values.[34]

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

[34] 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.

dividend by a certain value.[35] We apply this screen also to the U.S. dataset, although this issue is not of practical relevance there.

A.1.1. Constituent lists for the U.S. sample

We collect data from the following list types: research lists (FUSAA, FUSAB, FUSAC, FUSAD, FUSAE, FUSAF, FUSAG)[36], 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).[37,38]

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, DEADSD (Sweden); WSCOPESW, FSWS, DEADSW (Switzerland); WSCOPETK,

[35] 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 U.S. 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.

[36] 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.

[37] The lists "FUSAA, FUSAB, …, FUSAG", "DEADUS1, DEADUS2, …, DEADUS6" and "WSUS1, WSUS2, …, WSUS18" are special constituent list of all available firms availiable provided by TRD and TRW.

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

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.[39]

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.

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

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).

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.[40] 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.[41]

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

[40] 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 U.S. dataset. For other countries a different time span is used.
[41] 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.

six portfolios, which are held for one year.[42] Panel A of Table A.10 illustrates the sorting procedure.

[Table A.10 here]

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

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

Error! Bookmark not defined. $$\mathrm{HML}_t = \frac{\mathrm{r}_t^{S/H} + \mathrm{r}_t^{B/H}}{2} - \frac{\mathrm{r}_t^{S/L} + \mathrm{r}_t^{B/L}}{2}.$$

(A.2)

$\mathrm{r}_t^{X/Y}$ 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.[43] 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.

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[42] 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.
[43] Mean returns in this case are based on a geometric mean, as it is common in the literature.

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 U.S., 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.[44] The rationale behind this procedure is to limit the influence of microcaps and small stocks (see also Hou, Xue and Zhang, 2014). 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

[44] 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.

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]

In addition, we also report in the same manner as described above the breakpoints for the ten U.S. size portfolios (Table A.12), the ten U.S. BE/ME portfolios (Table A.13), the ten U.S. momentum portolios (Table A.14), the 25 U.S. 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 sample, we sort all sample 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 sample according to their size and allocate them into ten size groups according to the empirical breakpoints inferred from the FF data, as described in Section 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 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 groups, again by employing decile breakpoints (see Table A.14). The ten momentum groups of each sample show an almost monotonic behavior between momentum and average returns. The average return of the tenth group for the TRD sample is substantially higher than the average returns in the FF sample. The correlations of the momentum groups range between 0.84 and 0.92.

[Table A.17 here]

We also compute the ten size, BE/ME and momentum deciles from the simply screened data (see section 2.2.2). The outcome is shown in Table A.18. 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.

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

Panel A of Table A.19 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 the TRD and TRW and FF size-BE/ME return series can be found in the small size/low BE/ME group.[45] For the second and third BE/ME group

[45] 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 smaller). 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

there seems to be almost 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 groups and low returns in the big size groups can be observed in both samples. The correlations of the 25 size-BE/ME TRD and TRW portfolios with the 25 size-BE/ME FF 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.19 here]

We report the results for 25 size-momentum portfolios in the panel B of Table A.19. 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 the TRD 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 loser portfolio. The correlations of the twenty-five size-momentum returns between the FF- and the TRD sample range between 0.87 and 0.95.

In sum, this benchmark exercise confirms that TRD and TRW data can be used to construct the Fama-French factors SMB and HML as well as the Carhart factor WML to obtain factor data very similar to the version provided by Kenneth French. Furthermore, test portfolios, sorted on single characteristics as well as joint sorts on two characteristics are similar to the Kenneth

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 A.17. 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.

French versions. While this is not surprising per se, it is a comforting baseline result that increases confidence in the ability to construct accurate common risk factors also for other countries across the globe.

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 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 U.S., 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 U.S.. 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]

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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 U.S.$. Lee removes observations with end of year prices below the 2.5 per cent quantile. For example, Ince and Porter report that removing prices below 0.1 U.S.$ 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 TRD 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 TRD 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 U.S. 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	447	268		
1985	636	484	284		
1986	721	527	311		
1987	894	643	364	196	308
1988	1,002	814	398	234	361
1989	2,304	1,040	513	240	389
1990	3,307	1,365	621	262	507
1991	3,505	1,333	638	287	613
1992	3,668	1,235	668	299	631
1993	3,871	1,253	713	301	670
1994	4,193	1,356	795	323	704
1995	4,402	1,348	834	333	786
1996	4,632	1,324	880	379	818
1997	4,985	1,364	960	397	858
1998	5,370	1,368	1,032	422	936
1999	5,584	1,311	1,059	587	999
2000	5,858	1,324	1,099	743	1,024
2001	6,313	1,291	1,136	809	1,040
2002	6,453	1,216	1,135	860	1,087
2003	6,589	1,211	1,156	955	1,096
2004	6,799	1,238	1,166	972	1,094
2005	7,068	1,280	1,205	1,044	1,107
2006	7,301	1,319	1,233	1,104	1,143
2007	7,512	1,277	1,193	1,109	1,139
2008	7,790	1,181	1,129	1,056	1,082
2009	7,900	1,083	1,045	994	1,029
2010	8,023	1,013	990	943	971
2011	8,519	1,042	930	857	887
All	8,765	3,662	1,919	1,906	1,914

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 U.S. 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 U.S. 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 U.S.$.

Table A.18: One way sorts on size, BE/ME and momentum for the U.S. 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: In this table, we report descriptive statistics for the time series of ten size, BE/ME, and momentum groups. We compare two different U.S. 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), 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 U.S.$.

Table A.19: Two way sorts on size-BE/ME and size-momentum for the U.S. 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 25 size-BE/ME (Panel A) and size-momentum portfolios (Panel B). We compare two different U.S. 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 U.S.$.

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
U.S.	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
U.S.	TBill	3 month		USGBILL3	U.S. TREASURY BILL RATE - 3 MONTH (EP)

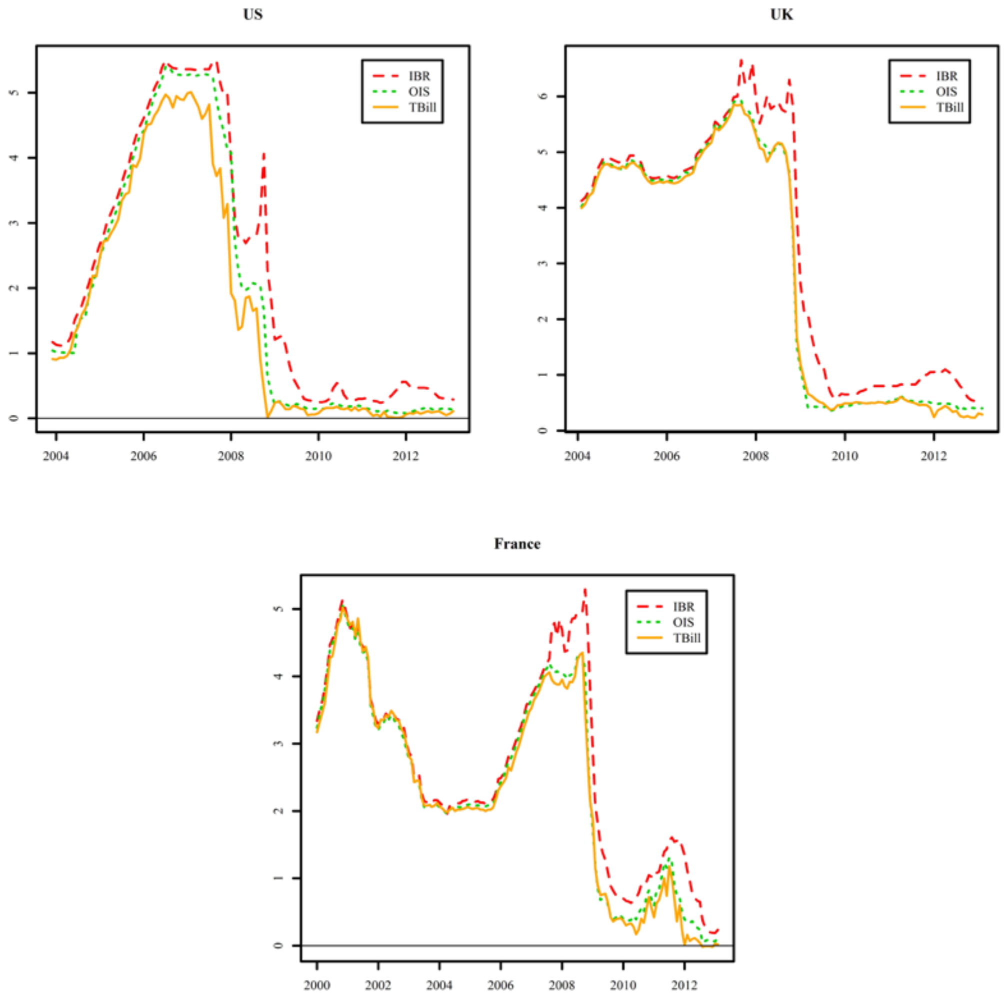
Note: This Table shows how the riskfree rate proxies for each country are composed. The following abbreviations are used: Treasury bill – TBill, interbank rate – IBR, overnight indexed swap - OIS. Source: TRD and Bank of Japan.

Table A.22: Countries ranked on market capitalization

Rank	Country	Market Cap.
1	U.S.	16,542,094.86
2	Japan	3,808,949.09
3	UK	3,024,832.69
4	France	2,077,363.46
5	Canada	1,954,319.04
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 U.S.$ in June 2011. The data are from TRD.

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



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