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Common risk factors in international stock markets

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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 often not realizable or at least significantly eroded due to transaction costs.

Keywords Risk factors · Value · Size · Momentum · Profitability · Investment · International equity markets · Asset pricing anomalies · Trading costs

JEL Classification C89 · G12 · G15

1 Introduction

Many path-breaking results in empirical finance have been established for US 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 discus-

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sion 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 USA that stocks having performed well in the past 12 months perform significantly better in the next 3–12 months than stocks which have performed poorly in the past 12 months. In applications, researchers frequently add a momentum factor to the Fama–French model, when modeling expected returns. Since Carhart (1997) employed this model originally, it is often referred to as the Carhart (1997) four-factor model.[1] Moreover, more recently expanded factor models have been introduced, which are also frequently employed by researchers (Fama and French 2015; Hou et al. 2015).

Researchers and practitioners alike are increasingly eager to determine the existence or non-existence of these anomalies in markets outside of the USA 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 USA), international data can address a common objection that anomalies observed in the US 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-US 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 paper 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 USA 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 Fama and French (1993, 2015), Carhart (1997), and Hou et al. (2015), including the market, value (HML—high-minus-low), size (SMB—small-minus-big), momentum (WML—winners-minus-losers), profitability (RMW—robust-minus-weak) and investment (CMA—conservative-minus-aggressive) risk factors, can be derived.

Importantly, in contrast to other datasets, we provide these factors on a country level (e.g., Kenneth French's data library provides the factors only on a regional level). In addition, these guidelines also apply to the construction of test portfolios, as it is done in the application-part of the paper (Sect. 3). The importance of using clean data is—at least—equally important when constructing test portfolios as when constructing factors.

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

[1] For an application of the Carhart (1997) four-factor model, see Asness et al. (2013) for example.

made in the construction, as well as a set of consistency checks hopefully ensure a particularly high level of reliability of the data we provide.[2,3]

We use TRD data (which mainly cover stock market data such as prices and dividends) and TRW data (which mainly cover accounting data such as common equity). It is well known that data from TRD 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 USA. 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 suggest additional screens, which are necessary to construct a reliable dataset (e.g., how to correct dividends properly).

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 USA, based on TRD and TRW data with important benchmarks, namely the market returns and momentum, size, value, profitability and investment 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).[4] We find that our market returns and risk factors for the USA and for Japan are generally very similar to the FF counterparts. For Europe, the market returns and the momentum factor are also very similar to the FF factors; the factors using accounting data also have high correlations, but exhibit some distinct patterns. Second, the reliability of our dataset is strengthened by additional comparisons for US 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.

[2] Some studies use proprietary, country-specific datasets which are in general inaccessible to other researchers, while other studies compile datasets from various sources. Griffin (2002), for example, uses data from the Pacific-Basin Capital Markets database (Japan), TRD (U.K. and Canada) and CRSP/COMPUSTAT (USA). Schrimpf et al. (2007) and Ziegler et al. (2007) use a database maintained at Humboldt University, Berlin, Germany. Further country-specific studies include Ammann and Steiner (2008) (Switzerland), Artmann et al. (2012) (Germany), Dimson et al. (2003), Gregory et al. (2009), Nagel (2001) (all three U.K.). Additional examples of studies that have employed non-US data to study empirical asset pricing models include, besides the studies already mentioned, An and Ng (2010), Ang et al. (2009), 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, b), 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. Different from this paper, Fama and French (2012) employ factors on the regional level, whereas we employ factors on the country level. Asness and Frazzini (2013) focus on the construction of the HML factors, whereas our focus is on data issues in general.

[3] 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. (2015) 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.

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

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.[5] 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 USA), though recent work argues that after controlling for differential cash flow shocks the size effect reappears (Hou and van Dijk 2019). 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.

Our main results on the profitability of size are as follows. First, we do not find a significant size effect for any of the countries covered, when judged by the average return on the SMB factors. However, Banz (1981) already suggested that "the size effect is not linear in the market value; the main effect occurs for very small firms while there is little difference in return between average sized and large firms" (p. 3). Consequently, we consider an "extreme" size effect, namely the difference in stock returns between the biggest 10% (in terms of market capitalization) and the smallest 10%. We find that the size effect (not adjusted for trading costs), when defined this way, appears to be alive and well in several of the countries we consider. Indeed, it also exists in several 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 incorporate a measure of trading costs and examine therefore the actual implementability of size-based trading strategies. We find that size premiums are most likely not realizable because the trading costs for the small size stocks are prohibitively high.

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

2 Data

Section 2.1 describes briefly the data preparation process and the construction of the risk factors proposed by Fama and French (1993, 2015), Carhart (1997) and Hou et al. (2015). A detailed treatment is given in the Online Appendix to the paper. Section 2.2 compares US market returns and common risk factors from our dataset with the corresponding series from Kenneth French's website. Section 2.3 conducts checks for the non-US markets. We compare self-created local market indexes with publicly available local market indexes (Sect. 2.3.1). While this exercise is usually not 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

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

pan-European as well as Japanese stock market returns and common risk factors from our dataset and compare them with another publicly available dataset (Sect. 2.3.2).

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 are in principle available from 1980 onwards, we 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 1991 (with book equity values from 1990) to 2018 for the USA and for most of the other countries (coverage for some countries is too limited before 1990). 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 select only observations when the security is active, correct for inconsistencies between price and dividend currencies, truncate a certain proportion at the lower end of the market value as well as the (unadjusted) price distribution, or perform sanity checks whether some TRD calculations do make sense, among other checks. 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 the Online Appendix.

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). Recently, two other, closely related, factor models have been proposed (Fama and French 2015; Hou et al. 2015). In this paper, we closely reproduce the factors in the manner of Fama and French (1993, 2015) and Hou et al. (2015). A detailed account of the construction of the SMB, HML, RMW, CMA, and WML factors is given in the Online Appendix A.2. Furthermore, we use the 3-month Treasury bill rate as the risk-free rate proxy. For countries where no Treasury bill is available, we usually use a combination of the interbank rate and the overnight indexed swap (OIS) rate. For details, see the Online Appendix.

2.2 Results for the US stock market

To confirm the quality of the common risk factors and test portfolios compiled using TRD, we compare these data with the well-known data provided by Kenneth French. Table 1 shows averages (avg.), standard deviations (σ) and t-statistics (t) for value-weighted US market returns from the FF and our TRD and TRW datasets as well

[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, pp. 466, 471).

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

	FF			TR			
	Avg. (1)	σ (2)	t (3)	Avg. (4)	σ (5)	t (6)	ρ (7)
VW	0.67	4.21	2.94	0.72	4.17	3.19	1.00
SMB	0.13	3.05	0.78	0.22	2.60	1.56	0.97
HML	0.18	2.97	1.13	0.23	3.21	1.30	0.94
RMW	0.36	2.62	2.56	0.32	2.57	2.30	0.44
CMA	0.21	2.07	1.84	0.18	2.04	1.66	0.92
WML	0.57	4.75	2.23	0.47	4.96	1.75	0.99

This table reports descriptive statistics for the time series of monthly value-weighted (VW) market excess returns as well as the returns of the SMB, HML, RMW, CMA, and WML factors. We compare two different US datasets with each other: the one provided by Kenneth French (FF) and our own dataset, compiled with TRD and TRW data (TR) as described in Sect. 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 07/1991 to 02/2018. All returns are in percent per month and are denominated in US$

as correlations between both return series (ρ) over time. The value-weighted market excess returns are quite similar, with an average monthly return of 0.67% for the FF series and an average monthly return of 0.72% for our series using TRD data. The correlation coefficient between the two value-weighted returns is 1.00.

We next analyze the time series of the SMB, HML, RMW, CMA, and WML factors for the USA The corresponding results are also shown in Table 1. The average values for the SMB factors are rather low and amount to 0.13% per month (FF data) and 0.22% (TRD and TRW data). The correlation coefficient between the two SMB factors based on the FF and our TRD and TRW dataset is 0.97. The HML factors yield slightly higher average values than the SMB factors and are very similar with 0.18% per month for the FF dataset and 0.23% per month for our dataset. The correlation coefficient between the two HML factors is 0.94. The RMW factors are even higher with 0.36% per month for the FF dataset and 0.32% per month for our dataset. However, the correlation between the two RMW factors is rather low, with only 0.44. This low correlation is likely due to differences in the underlying accounting data.[7] The CMA factors show average returns of 0.21%, and 0.18% per month for the two datasets, respectively. The correlation of the CMA factors is 0.92. The WML factors have rather high average values with 0.57% per month (FF data) and 0.47% per month (TRD and TRW data). The correlation coefficient between both factors is 0.99.

[7] For example, when constructing operating profitability, the underlying characteristic for RMW, we set missing sales, costs of goods sold, selling or administrative expenses and research & development expenses values equal to zero. To the extent that the database used in the FF dataset contains different values for these or other datapoints, this will induce differences in the ultimate results. If we leave aside R&D expenses completely, the correlation for RMW is 0.81.

In sum, we are able to replicate 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 the Online Appendix that test portfolios, sorted on single characteristics as well as jointly sorted on two characteristics are similar to the versions by Kenneth French.

2.3 Results for international stock markets

2.3.1 Market returns for single countries

To evaluate the quality of our dataset, we compare self-created market indexes from different countries with market indexes available on TRD. In Table 2, we present results for the market returns of twenty-nine countries. We report monthly average percentage values of known local indexes 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 indexes. Two time periods are examined: A long period (07/1989–03/2018) and a short period (07/1999–03/2018).[8]

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, some local indexes incorporate only price information, but not dividends. When this is the case, we calculate the comparison indexes with prices only. When possible, we use TRD total return indexes, which include dividend payments.[9] The third difference is that indexes like FTSE or MSCI do not include all stocks available because of the limited investability of small stocks. The remaining indexes are either broad market indexes (BAS (Belgium), TT (Canada), ISEQ (Ireland), TOPIX (Japan), SPI (Switzerland), WGI (Poland), ICEX-ALL (Iceland)); indexes restricted to a certain number of firms (CAC40 (France), AEX (Netherlands), RUSSELL (USA), LUXX (Luxembourg)); or indexes which cover a certain portion of the total market capitalization (HS (Hong Kong), SAX (Slovakia)).

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

[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. Exemptions are indicated in Table 2.

[9] The Swiss Performance index (SPI), the Warsaw General Index (WGI), The Share Index of the Budapest Stock Exchange (BUX), and the Slovak Share Index (SAX) include dividend payments by construction. Furthermore, we use total return indexes 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), USA (both periods), Luxembourg (second period), Greece (both periods), Hungary (both periods), and Czech Republic (both periods). All other indexes are pure price indexes.

Table 2 Comparison with international indexes

	Avg.			ρ		Avg.			ρ	
	Com. (1)	VW (2)	EW (3)	VW (4)	EW (5)	Com. (6)	VW (7)	EW (8)	VW (9)	EW (10)
Panel A:	07/1989–03/2018					07/1999–03/2018				
Australia (MSCI)	0.81	0.85	1.21	0.96	0.61	0.72	0.71	1.01	0.96	0.60
Austria (FTSE)	0.56	0.48	0.77	0.96	0.83	0.74	0.73	0.90	0.97	0.80
Belgium (BAS)	0.45	0.48	0.79	0.91	0.82	0.26	0.35	0.75	0.95	0.80
Canada (TT)	0.70	0.81	1.54	0.98	0.78	0.63	0.72	1.45	0.98	0.79
Denmark (FTSE)	0.81	0.75	0.81	0.97	0.71	1.02	1.06	0.85	0.98	0.74
Finland (FTSE)	0.88	0.49	1.11	0.89	0.69	0.56	0.67	1.01	0.99	0.67
France (CAC40)	0.72	0.74	1.08	0.98	0.74	0.45	0.58	1.19	0.99	0.77
Germany (FTSE)	0.61	0.52	0.70	0.98	0.75	0.60	0.56	0.64	0.98	0.75
Hong Kong (HS)	1.01	0.94	1.52	0.98	0.73	0.83	0.77	1.40	0.98	0.69
Ireland (ISEQ)	0.78	0.68	1.00	0.95	0.77	0.49	0.47	1.07	0.94	0.77
Italy (FTSE)	0.34	0.56	0.60	0.96	0.87	0.27	0.35	0.49	0.99	0.87
Japan (TOPIX)	0.16	0.20	0.68	1.00	0.85	0.34	0.38	0.99	1.00	0.83
Netherlands (AEX)	0.80	0.80	0.82	0.98	0.82	0.40	0.48	0.72	0.99	0.82
Norway (FTSE)	0.65	0.65	1.12	0.97	0.79	0.95	0.98	0.98	0.98	0.81
Portugal (MSCI)	0.47	0.57	0.91	0.95	0.73	0.09	0.32	0.77	0.95	0.69
Singapore (MSCI)	0.66	0.70	1.14	0.96	0.82	0.57	0.57	0.79	0.97	0.80
Spain (FTSE)	0.50	0.26	0.73	0.94	0.82	0.47	0.46	0.53	0.98	0.77
Sweden (FTSE)	0.87	0.82	1.12	0.97	0.78	0.78	0.82	1.08	0.99	0.80
Switzerland (SPI)	0.75	0.77	0.79	0.99	0.81	0.44	0.45	0.77	0.99	0.81
Turkey (MSCI)	3.90	4.49	4.64	0.92	0.90	2.19	2.16	2.76	0.99	0.89
U.K. (FTSE)	0.75	0.74	0.58	1.00	0.72	0.49	0.51	0.50	1.00	0.72

Table 2 continued

	Avg.			ρ		Avg.			ρ	
	Com. (1)	VW (2)	EW (3)	VW (4)	EW (5)	Com. (6)	VW (7)	EW (8)	VW (9)	EW (10)
USA (RUSSELL)	0.89	0.95	1.57	1.00	0.86	0.59	0.65	1.50	1.00	0.88
Panel B:	01/1992–06/1999					07/1999–03/2018				
Luxembourg (MSCI/LUXX)	1.07	1.29	1.65	0.62	0.52	0.58	0.54	0.77	0.70	0.59
Panel C:	03/1992–03/2018									
Greece (MSCI)	0.16	0.27	1.40	0.91	0.67	− 0.69	− 0.60	0.54	0.88	0.65
Panel D:	02/1993–03/2018									
Poland (WGI)	1.94	1.56	2.16	0.97	0.92	0.78	0.67	1.18	0.99	0.81
Hungary (MSCI)	1.61	1.65	1.46	0.99	0.72	0.99	0.86	1.07	0.99	0.64
Panel E:	08/1996–03/2018									
Czech Republic (FTSE)	0.79	0.94	1.19	0.98	0.53	0.97	1.08	1.45	0.97	0.45
Panel F:										
Slovakia (SAX)						0.80	1.12	1.67	0.84	0.74
Panel G:						01/2001–03/2018				
Iceland (ICEXALL)						0.46	1.05	0.98	0.84	0.74

In this table, we report 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, ranging from 07/1989 to 03/2018, and a short one, ranging from 07/1999 to 03/2018, exceptions are indicated. We use the following country-specific indexes for comparison: MSCI (Australia, Portugal, Singapore, Turkey, Luxembourg, Greece), FTSE (Austria, Denmark, Finland, Germany, Italy, Norway, Sweden, U.K., 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), Madrid SE General (IGBM, Spain), Swiss Performance Index (SPI, Switzerland), Russell 3000 (RUSSELL, USA), Hang Seng (HS, Hong Kong), Luxembourg Stock Exchange Index (LUXX, Luxembourg), 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

The main result of this analysis is that for all big international stock markets the correlations of our value-weighted market returns with the local indexes are quite high. Only smaller markets, like Luxembourg, Slovakia, and Iceland, show rather low correlation figures ranging from 0.62 to 0.84. Furthermore, it is a satisfying result that for the biggest stock markets our indexes are almost perfectly correlated with the benchmark indexes. The bigger stock markets (e.g., USA, Japan, U.K., France, Canada, Germany, Hong Kong, Australia, Switzerland, Spain, Italy, the Netherlands, and Sweden), all have at least correlations of 0.96 (0.94) in the period 07/1999–03/2018 (07/1989–03/2018) with the respective benchmarks. Correlation coefficients in all countries are at least 0.89 (0.88) for the long (short) period except for Luxembourg, Slovakia, and Iceland (data are only available for the short period).[10]

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

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

Panel A of Table 3 shows averages (avg.), standard deviations (σ) and t-statistics (t) for value-weighted pan-European market excess returns from the FF and our TRD and TRW datasets as well as correlations between both return series (ρ) over time. The value-weighted market returns are similar for both datasets and on average 0.59% per month for the FF data and 0.66% for our data. The correlation of the two series is 0.96.

For the Japanese dataset as shown in Panel B of Table 3, we also obtain similar average value-weighted market excess returns, with 0.15% for the FF data and 0.14% for our data. The correlation is 1.00.

We next compile overall common risk factors. The results are also shown in Table 3. In Europe, the average returns for the SMB factor are not statistically different from zero with 0.10% (FF data) versus − 0.09% (our TRD and TRW data). The average returns of the HML factor are very similar with 0.36% (FF data) versus 0.27 (our TRD and TRW data). The correlations for the two factors are a bit lower than for the USA, amounting to 0.70 (SMB) and 0.62 (HML). The RMW factor shows somewhat different average returns of 0.37% (FF data) and 0.12% (TRD/TRW data) and a rather low correlation, as in the USA, of 0.43. By contrast, the average returns of the CMA factor are rather close with 0.21% (FF data) and 0.28% (TRD/TRW data), and a correlation of 0.55. The average returns for the WML factor are 0.95% (FF data) and 1.04% (TRD/TRW data), and the correlation is a bit lower than for the USA, but also rather high, amounting to 0.88.

For Japan, the average SMB, HML, RMW, and CMA returns are also a bit more dispersed than for the US sample, but still point into the same direction, and show

[10] We suspect that the relatively low correlation of our indexes with the comparison indexes 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.

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

	FF			TR			
	Avg. (1)	σ (2)	t (3)	Avg. (4)	σ (5)	t (6)	ρ (7)
Panel A: Europe							
VW	0.59	4.83	2.19	0.66	5.22	2.26	0.97
SMB	0.10	2.17	0.83	− 0.09	2.87	− 0.59	0.70
HML	0.36	2.43	2.63	0.27	2.63	1.86	0.62
RMW	0.37	1.60	4.11	0.12	2.27	0.92	0.43
CMA	0.21	1.83	2.03	0.31	2.28	2.45	0.55
WML	0.95	3.97	4.30	1.04	4.13	4.51	0.88
Panel B: Japan							
VW	0.15	5.46	0.50	0.14	5.45	0.46	1.00
SMB	0.15	3.16	0.85	0.09	2.93	0.53	0.98
HML	0.34	2.91	2.06	0.43	2.58	3.00	0.74
RMW	0.09	2.18	0.75	0.31	2.56	2.13	0.72
CMA	0.08	2.41	0.61	0.04	2.02	0.38	0.83
WML	0.16	4.39	0.66	0.21	4.68	0.80	0.97

This table reports descriptive statistics for the time series of monthly value-weighted (VW) market excess returns as well as the returns of the SMB, HML, RMW, CMA, and WML factors. We compare two different datasets with each other: The one provided by Kenneth French (FF) and our own dataset, compiled with TRD and TRW data (TR) as described in Sect. 2.1. Panel A shows the factors for Europe, whereas panel B shows the corresponding factors for Japan. 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 7/1991 to 02/2018. Average returns are in percent per month and are denominated in US$

higher correlations than the European sample. The average SMB return is 0.15% for the FF data and 0.09% for our data. The correlation of the two SMB versions is 0.98. The average return figures for HML are 0.34% (FF data) and 0.43% (our TRD and TRW data), with a correlation of 0.74. The average return of the RMW factor is 0.09% for the FF data and 0.31% for our dataset. The corresponding correlation is 0.72. For the CMA factor, we observe rather similar averages of 0.08% and 0.04% and a correlation of 0.83. The average WML return is 0.16% for the FF data and 0.21% for our data. The correlation of the two series is 0.97. 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, these findings show that while some factors (in particular the Market factor and WML) are very similar to the FF versions in all three regions (USA, Europe, and Japan), for the factors that incorporate accounting data, there are some differences, especially in Europe.

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 the Online Appendix.[11] 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.[12]

For the first approach, we calculate the mean returns of the SMB factors and report the corresponding t-statistics. Since factor risk premiums can be estimated by means when factors are excess returns (Cochrane 2005, p. 231), this is one possibility to test for a size premium. Columns (1) and (2) of Table 4 display the results.[13] A positive mean return of the SMB factor is obtained for five of the 14 examined countries. However, none of these mean returns are significantly different from zero on a ten percent level. These results suggest that the size effect may have been eroded over time.

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 and five-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 et al. (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. The idea of variation (1) is to give more weight to the smaller size groups, since in the sort with equal breakpoints most of these groups are populated with rather tiny stocks. Variation (2) is often applied in other studies (e.g., De Moor and Sercu 2013)

[11] Note that NYSE breakpoints may result in a very uneven distribution of stocks across the different portfolio groups.

[12] By referring to *equal breakpoints*, we construct decile or quintile sorts by constructing groups with an approximate equal size. For a detailed account, see section A.2.2 in the Online Appendix.

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

Table 4 Size returns

	SMB		1–10 (NYSE BPs)		1–10 (Equal BPs)		1–5 (Equal BPs)	
	Mean (1)	t (2)	Mean (3)	t (4)	Mean (5)	t (6)	Mean (7)	t (8)
Australia	– 0.15	– 0.90	– 0.26	– 0.85	1.53	3.61	0.76	2.06
Austria							– 0.28	– 0.88
Belgium							– 0.56	– 1.65
Canada	0.01	0.07	0.58	2.07	1.40	4.11	0.96	3.20
Denmark	– 0.43	– 1.93	– 0.29	– 1.03	– 0.13	– 0.43	– 0.03	– 0.13
Finland							– 0.10	– 0.24
France	0.02	0.13	– 0.18	– 0.77	0.41	1.30	– 0.16	– 0.65
Germany	– 0.27	– 1.43	– 0.53	– 2.15	0.08	0.24	– 0.39	– 1.44
Greece							1.57	2.65
Hong Kong	– 0.27	– 1.00	0.20	0.49	1.33	2.60	0.83	1.83
Ireland							0.19	0.36
Italy	0.01	0.06	– 0.34	– 1.30	– 0.11	– 0.30	– 0.10	– 0.34
Japan	– 0.03	– 0.17	0.25	0.98	0.76	2.90	0.50	2.07
Netherlands	– 0.11	– 0.64	0.04	0.17	– 0.02	– 0.05	– 0.01	– 0.03
Norway	– 0.01	– 0.04	– 0.28	– 0.94	0.75	2.01	0.04	0.13
Poland							0.22	0.37
Singapore	– 0.31	– 1.59	0.18	0.51	1.28	2.81	0.55	1.30
Spain							– 0.14	– 0.50
Sweden							– 0.55	– 1.55
Switzerland	0.01	0.09	0.15	0.68	0.19	0.74	0.00	0.01
Turkey							0.43	0.86
U.K.	0.00	0.02	– 0.45	– 1.76	0.16	0.55	– 0.35	– 1.33
USA	0.23	1.54	0.71	2.97	1.36	5.46	1.01	4.23

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). Two versions of the mean return as well as the corresponding t-statistics of the 1–10 spread are provided: One with breakpoints based on the approximate NYSE breakpoints (columns (3) and (4) marked with "NYSE BPs") and one with equal breakpoints (columns (5) and (6) marked with "Equal BPs"; see also the online 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 domestic currency. We use the following time periods: 07/1991-02/2018: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, U.K., U.S.; 07/2000-02/2018: Hong Kong; 07/1993-02/2018: Norway; 10/1995-02/2018: Poland; 07/2006-02/2018: Turkey

and represents an extreme case, since it is highly dependent on tiny stocks. In addition, we report results for variant (3) to be able consider a larger number of countries.[14]

[14] 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.

In each case, we construct a portfolio long in the smallest group and short in the biggest group of stocks for each country. For example, in the case of the decile spread 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:

$$(r_t^1 - r_t^{10}) = \alpha + \beta_M \cdot (r_{M,t} - r_{f,t}) + \beta_{\text{SMB}} \cdot \text{SMB}_t + \beta_{\text{HML}} \cdot \text{HML}_t + \beta_{\text{WML}} \cdot \text{WML}_t + \varepsilon_t, \tag{1}$$

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 risk-free rate proxy in time t, SMB_t, HML_t, and WML_t are the factors as described in greater detail in the Online Appendix, 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.

In addition, we also estimate five-factor alphas according to Fama and French (2015):

$$(r_t^1 - r_t^{10}) = \alpha^{FF5} + \beta_M^{FF5} \cdot (r_{M,t} - r_{f,t}) + \beta_{\text{SMB}}^{FF5} \cdot \text{SMB}_t^{FF5} + \beta_{\text{HML}}^{FF5} \cdot \text{HML}_t + \beta_{\text{RMW}} \cdot \text{RMW}_t + \beta_{\text{CMA}} \cdot \text{CMA}_t + \varepsilon_t^{FF5}. \tag{2}$$

Therefore, the factors RMW and CMA are added to the Fama–French three-factor model. The SMB factor is modified as described in section A.2.1. of the Online Appendix.

First, we present results for the 1–10 size spread portfolio which is based on (approximate) NYSE breakpoints (see the Online Appendix A.2.2). This approach of constructing size deciles is akin to the approach of Fama and French (1992), who use NYSE breakpoints. The results for the raw returns are shown in columns (3) and (4) of Table 4. Seven out of 14 countries show a positive size premium, and two of them (Canada and USA) are positive and significant (5% level), whereas for one other country the size premium is negative and significant (Germany). The results for the estimated four-factor and five-factor alphas are depicted in columns (1) and (2) of Table 5. As expected, correcting for the risk factors lowers the estimated size premiums and also the t-statistics. Here, seven (eight, for the five-factor model) out of 14 countries show a positively estimated size premium, but only the Canadian, Hong Kong, and Japanese premiums (for the five-factor model) and the US premium (both models) is significant (5% level), whereas the U.K. (both models) size premium is significantly negative (5% level).

Second, we present the results for the 1–10 size spread with equal breakpoints. Columns (5) and (6) of Table 4 show that the size premiums are greater than zero for

Even with equal breakpoints this portfolio would contain only 3–6 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.

all countries except Denmark, Italy and the Netherlands and significant (5% level) for seven out of fourteen countries. The estimated four-factor alphas, shown in columns (3) and (4) of Table 5, are greater than zero for all countries examined and different from zero at the 5% significance level for eight (nine) out of 14 countries, for the four-factor (five-factor) model.

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. 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.[15]

We now discuss the results of the quintile spread. The results for the raw returns are shown in columns (7) and (8) of Table 4. The average returns of the quintile spreads have the same sign as the decile spreads (with three exceptions: France, Germany and the U.K.), and the magnitude of the average returns is in general lower than for the decile spreads. Twelve premiums are positive, and five out of 23 country premiums are positive and significant (5% level). In Table 5, we report results for two different versions of the factors to estimate four-factor and five-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 French, German and U.K. size premiums are positive, and 3 (7 in case of the five-factor model) out of 14 country premiums are positive and significant (5% level). Columns (7) and (8) show the estimated four-factor alphas of the size quintiles with factors constructed using equal breakpoints. For the additional nine countries, only the Greek four- and five-factor alphas are positive and significant (5% level). Overall, out of 23 countries 15 (16 for the five-factor model) estimated size premiums are positive and four (six for the five-factor model) of them are significant (5% level).

In the Online Appendix, we report results for the Hou-Xue-Zhang model as well as results for all three models without the SMB factor. By and large, the results do not change substantially.

In sum, these results show that size premiums, when they exist, are driven by the smallest 10–20% of stocks and that there are considerable differences across countries. We note that the returns from these strategies can be rather substantial. In particular, the returns for the 1–10 spread with equal breakpoints are up to 1.53% per month in the case of Australia, which is about 20% annually. Other major markets like Canada, the USA, or Hong Kong also show substantial returns with 1.40%, 1.36%, and 1.33% (about 18%, 18%, and 17% annually). By way of comparison, the market excess return for the USA is about 0.67% (8% annually) over the same period.

The results discussed above reveal a material difference between the approaches using approximate NYSE breakpoints and equal breakpoints. The reason for this is that

15 Fama (1998, p. 296) makes the case for using value-weighted returns. He argues that value-weighted returns capture more accurately the total wealth effects experienced by investors. Furthermore, he is concerned that using equal-weighted returns may amplify model problems. Novy-Marx and Velikov (2016, p. 106) 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.

Table 5 Risk-adjusted size returns

	1–10				1–5			
	Car NYSE BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs Equal BP factors	FF5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Australia	−0.32	−0.14	1.63	1.72	0.69	0.88	0.73	0.75
	(−1.17)	(−0.66)	(3.56)	(4.57)	(1.86)	(2.65)	(2.31)	(2.30)
Austria							−0.04	−0.13
							(−0.17)	(−0.61)
Belgium							−0.27	−0.25
							(−0.72)	(−0.76)
Canada	0.34	0.56	1.28	1.49	0.77	0.96	0.39	0.58
	(1.70)	(2.97)	(4.38)	(5.09)	(3.03)	(4.00)	(1.87)	(3.19)
Denmark	0.09	0.00	0.25	0.14	0.34	0.40	0.38	0.34
	(0.45)	(0.01)	(1.18)	(0.64)	(1.84)	(2.20)	(2.34)	(2.39)
Finland							0.23	0.01
							(1.19)	(0.08)
France	−0.18	−0.21	0.51	0.48	−0.08	−0.08	−0.03	−0.08
	(−1.62)	(−1.95)	(2.26)	(2.36)	(−0.57)	(−0.60)	(−0.26)	(−0.68)
Germany	−0.16	−0.13	0.39	0.34	−0.03	−0.06	−0.04	−0.00
	(−1.32)	(−1.29)	(1.38)	(1.24)	(−0.15)	(−0.30)	(−0.24)	(−0.01)
Greece							1.18	1.09
							(4.11)	(3.98)

Table 5 continued

	1–10				1–5			
	Car NYSE BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs Equal BP factors	FF5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hong Kong	−0.04	0.40	1.13	1.64	0.56	1.01	0.45	0.48
	(−0.22)	(2.43)	(3.05)	(3.83)	(1.81)	(3.04)	(1.94)	(1.81)
Ireland							0.65	0.20
							(1.47)	(0.51)
Italy	−0.27	−0.11	0.08	0.11	0.00	0.09	0.13	−0.00
	(−1.79)	(−0.80)	(0.29)	(0.40)	(0.01)	(0.48)	(0.80)	(−0.02)
Japan	0.10	0.12	0.61	0.36	0.36	0.35	0.18	0.17
	(1.40)	(1.98)	(4.58)	(4.96)	(3.18)	(3.35)	(2.26)	(2.65)
Netherlands	0.21	0.21	0.43	0.35	0.36	0.28	0.37	0.21
	(1.14)	(1.19)	(1.38)	(1.15)	(1.57)	(1.28)	(1.64)	(1.11)
Norway	−0.13	−0.26	0.98	0.90	0.19	0.16	0.04	0.16
	(−0.63)	(−1.37)	(3.25)	(3.17)	(0.79)	(0.72)	(0.17)	(0.74)
Poland							−0.40	0.31
							(−1.19)	(0.74)
Singapore	0.15	0.24	1.11	1.25	0.58	0.69	0.35	0.37
	(0.88)	(1.47)	(3.03)	(3.90)	(1.86)	(2.46)	(1.44)	(1.62)
Spain							0.09	0.08
							(0.43)	(0.43)
Sweden							−0.39	−0.48
							(−1.52)	(−2.00)

Table 5 continued

	1–10				1–5			
	Car NYSE BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs Equal BP factors	FF5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Switzerland	0.05	0.03	0.39	0.40	0.09	0.07	0.04	0.01
	(0.42)	(0.30)	(1.90)	(2.09)	(0.66)	(0.55)	(0.33)	(0.09)
Turkey							−0.02	0.14
							(−0.08)	(0.56)
U.K.	−0.58	−0.31	0.11	0.35	−0.48	−0.16	−0.30	−0.02
	(−3.99)	(−2.25)	(0.56)	(1.75)	(−2.81)	(−0.85)	(−2.06)	(−0.14)
USA	0.24	0.43	1.22	1.42	0.83	1.01	0.57	0.65
	(2.34)	(4.64)	(6.29)	(7.44)	(4.90)	(5.95)	(4.54)	(4.87)

We report Carhart four-factor alphas (Car) and Fama–French five-factor alphas (FF5) of a spread of a small decile and a large decile portfolio (using equal breakpoints). We provide two versions of the 1–10 spread: one with breakpoints based on the approximate NYSE breakpoints (columns (1) and (2); see also the Online Appendix A.2.2) and one equal breakpoints (columns (3) and (4)). Columns (5)–(8) report Carhart four-factor alphas (Car) and Fama–French five-factor alphas (FF5) of a spread of a small quintile and a large quintile portfolio (using equal breakpoints). In columns (1)–(6), we employ factors by applying approximate NYSE breakpoints. In columns (7) and (8), we employ 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 in parenthesis. t-statistics refer to the null that the alphas are zero. Alphas are in percent per month and are denominated in domestic currency. We use the following time periods: 07/1991–02/2018: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, U.K., USA; 07/2000–02/2018: Hong Kong; 07/1993–02/2018: Norway; 10/1995–02/2018: Poland; 07/2006–02/2018: Turkey the composition of the respective portfolios of these approaches is very different. For the case with approximative NYSE breakpoints for the USA, 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.[16] 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 or 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, our results are mostly driven by the small size portfolios, suggesting that a trading strategy may be difficult to implement. We address the question of practical implementability explicitly in Sect. 3.2.

3.2 International size premiums when adjusting for trading costs

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

To account for trading costs, we apply the trading cost measure proposed by Lesmond et al. (1999). These authors utilize the incidence of zero returns for the estimation of transaction costs. We describe this approach in greater detail in Sect. A.1 in the appendix. We assume that trading costs incur when stocks go in or out of a portfolio. When we calculate long-short portfolios, we subtract both the trading costs of the long and the short portfolio from the return of the resulting spread portfolio. Therefore, it is possible that negative returns, and also t-values, might occur that are big in absolute terms, but are *not* indicative of gains from the opposite position (that is, multiplying the long-short portfolio by -1).

Table 6 shows the results for the SMB portfolio as well as for the decile spread with NYSE breakpoints, the decile spread with equal breakpoints, and the quintile spread with equal breakpoints. The results show that most of the average returns and t-values are negative, and only a few ones remain positive and are insignificantly different from zero. This means that when accounting for trading costs, the size profits documented in Sect. 3.1 vanish. The only notable exemption are the USA Here, both decile spread and the quintile spread are positive and significant on the 5% level. However, the size premiums are diminished by a great deal, when compared to the unadjusted size premiums (e.g., the decile spread with equal breakpoints is about as half as big).

In Table 7, we show the trading cost-adjusted results when accounting for the four-factor and five-factor models. In general, the results are similar as for the average

[16] See Table A.12 of the Online Appendix.

Table 6 Size returns: trading cost adjusted

	SMB		1–10 (NYSE BPs)		1–10 (Equal BPs)		1–5 (Equal BPs)	
	Mean (1)	t (2)	Mean (3)	t (4)	Mean (5)	t (6)	Mean (7)	t (8)
Australia	− 0.52	− 2.90	− 1.39	− 3.81	− 2.40	− 3.42	− 1.38	− 3.11
Austria							− 1.15	− 3.20
Belgium							− 1.54	− 3.69
Canada	− 0.13	− 0.83	0.20	0.69	− 0.07	− 0.17	0.04	0.12
Denmark	− 0.71	− 3.21	− 0.60	− 2.12	− 2.01	− 2.53	− 1.06	− 3.01
Finland							− 0.45	− 1.07
France	− 0.27	− 1.44	− 1.09	− 3.78	− 8.41	− 2.31	− 3.10	− 4.35
Germany	− 0.49	− 2.52	− 0.99	− 3.73	− 1.42	− 3.09	− 1.40	− 3.68
Greece							1.07	1.79
Hong Kong	− 0.50	− 1.75	− 0.06	− 0.14	0.52	0.97	0.28	0.59
Ireland							− 0.87	− 1.48
Italy	− 0.05	− 0.26	− 0.40	− 1.53	− 0.30	− 0.82	− 0.24	− 0.83
Japan	− 0.12	− 0.77	0.16	0.63	0.46	1.75	0.31	1.28
Netherlands	− 0.19	− 1.12	− 0.04	− 0.15	− 2.54	− 1.42	− 0.91	− 1.26
Norway	− 0.21	− 1.05	− 0.53	− 1.82	0.04	0.11	− 0.50	− 1.49
Poland							− 0.39	− 0.65
Singapore	− 0.60	− 2.95	− 0.18	− 0.52	− 0.23	− 0.40	− 0.39	− 0.85
Spain							− 0.56	− 1.84
Sweden							− 1.13	− 3.12
Switzerland	− 0.11	− 0.61	0.05	0.24	− 0.37	− 1.33	− 0.27	− 1.24
Turkey							0.30	0.60
U.K.	− 0.17	− 0.84	− 1.03	− 3.68	− 1.91	− 4.89	− 1.54	− 5.01
USA	0.15	1.09	0.54	2.28	0.69	2.54	0.50	2.03

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). Two versions of the mean return as well as the corresponding t-statistics of the 1–10 spread are provided: One with breakpoints based on the approximate NYSE breakpoints (columns (3) and (4) marked with "NYSE BPs") and one with equal breakpoints (columns (5) and (6) marked with "Equal BPs"; see also the online 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 domestic currency. All returns are adjusted for trading cost by using the transaction cost measure of Lesmond et al. (1999). We use the following time periods: 07/1991-02/2018: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, U.K., U.S.; 07/2000-02/2018: Hong Kong; 07/1993-02/2018: Norway; 10/1995-02/2018: Poland; 07/2006-02/2018: Turkey

spread results. However, there are some exceptions: For Greece, we find positive and significant four-factor alphas for the quintile spread; for Hong Kong, we detect a positive and significant alpha for the decile spread (with equal breakpoints) and the five-factor model; for Japan, we document significant four- and five-factor alphas for

Table 7 Risk-adjusted size returns: trading cost adjusted

	1–10				1–5			
	Car NYSE BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs Equal BP factors	FF5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Australia	− 1.55	− 1.84	− 2.93	− 3.22	− 1.56	− 1.69	− 1.70	− 1.68
	(− 3.50)	(− 4.04)	(− 2.93)	(− 2.88)	(− 2.79)	(− 3.21)	(− 3.37)	(− 3.44)
Austria							− 0.92	− 0.96
							(− 3.15)	(− 3.60)
Belgium							− 1.39	− 1.27
							(− 2.83)	(− 2.96)
Canada	− 0.03	0.17	− 0.12	− 0.02	− 0.12	0.03	− 0.48	− 0.36
	(− 0.12)	(0.85)	(− 0.30)	(− 0.05)	(− 0.39)	(0.08)	(− 1.71)	(− 1.38)
Denmark	− 0.26	− 0.39	− 2.08	− 2.77	− 0.82	− 0.93	− 0.73	− 0.96
	(− 1.19)	(− 2.15)	(− 1.75)	(− 1.77)	(− 1.88)	(− 1.70)	(− 1.79)	(− 1.92)
Finland							− 0.10	− 0.33
							(− 0.47)	(− 1.65)
France	− 0.99	− 1.11	− 8.00	− 8.28	− 2.65	− 3.01	− 2.68	− 3.09
	(− 5.80)	(− 6.10)	(− 2.08)	(− 2.23)	(− 4.83)	(− 4.56)	(− 4.33)	(− 4.48)
Germany	− 0.58	− 0.58	− 1.13	− 1.33	− 0.90	− 1.03	− 0.92	− 0.97
	(− 3.66)	(− 3.64)	(− 2.57)	(− 2.57)	(− 3.04)	(− 2.78)	(− 3.31)	(− 2.72)
Greece							0.68	0.60
							(2.09)	(1.93)

Table 7 continued

	1–10				1–5			
	Car NYSE BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs Equal BP factors	FF5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hong Kong	− 0.24	0.22	0.48	1.04	0.12	0.60	− 0.01	0.06
	(− 1.46)	(1.28)	(1.29)	(2.42)	(0.38)	(1.72)	(− 0.05)	(0.22)
Ireland							− 0.37	− 0.86
							(− 0.68)	(− 1.70)
Italy	− 0.33	− 0.17	− 0.10	− 0.08	− 0.14	− 0.06	− 0.01	− 0.15
	(− 2.22)	(− 1.26)	(− 0.36)	(− 0.30)	(− 0.69)	(− 0.29)	(− 0.04)	(− 0.79)
Japan	0.02	0.03	0.32	0.33	0.18	0.18	− 0.01	0.00
	(0.23)	(0.57)	(2.33)	(2.52)	(1.54)	(1.59)	(− 0.07)	(− 0.01)
Netherlands	0.13	0.13	− 2.41	− 2.47	− 0.63	− 0.72	− 0.59	− 0.85
	(0.68)	(0.71)	(− 1.21)	(− 1.24)	(− 0.82)	(− 0.93)	(− 0.79)	(− 1.01)
Norway	− 0.40	− 0.52	0.24	0.18	− 0.37	− 0.40	− 0.54	− 0.40
	(− 1.90)	(− 2.74)	(0.76)	(0.59)	(− 1.42)	(− 1.71)	(− 2.14)	(− 1.69)
Poland							− 1.01	− 0.32
							(− 2.74)	(− 0.74)
Singapore	− 0.17	− 0.09	0.00	0.36	− 0.29	− 0.23	− 0.53	− 0.49
	(− 0.88)	(− 0.50)	(0.01)	(0.78)	(− 0.78)	(− 0.67)	(− 1.67)	(− 1.66)
Spain							− 0.33	− 0.33
							(− 1.49)	(− 1.68)
Sweden							− 0.98	− 1.08
							(− 3.72)	(− 4.36)

Table 7 continued

	1–10				1–5			
	Car NYSE BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs NYSE BP factors	FF5	Car Equal BPs Equal BP factors	FF5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Switzerland	−0.05	−0.07	−0.12	−0.18	−0.17	−0.21	−0.23	−0.28
	(−0.44)	(−0.69)	(−0.61)	(−0.87)	(−1.21)	(−1.51)	(−1.84)	(−2.43)
Turkey							−0.16	0.00
							(−0.58)	(0.01)
U.K.	−1.17	−0.89	−2.04	−1.59	−1.70	−1.28	−1.48	−1.14
	(−6.36)	(−4.92)	(−5.10)	(−4.82)	(−6.87)	(−5.45)	(−6.63)	(−5.75)
USA	0.09	0.21	0.61	0.63	0.33	0.35	0.11	0.17
	(0.82)	(2.31)	(2.56)	(2.60)	(1.71)	(1.83)	(0.71)	(1.05)

We report Carhart four-factor alphas (Car) and Fama–French five-factor alphas (FF5) of a spread of a small decile and a large decile portfolio (using equal breakpoints). We provide two versions of the 1–10 spread: one with breakpoints based on the approximate NYSE breakpoints (columns (1) and (2); see also the Online Appendix A.2.2) and one equal breakpoints (columns (3) and (4)). Columns (5)–(8) report Carhart four-factor alphas (Car) and Fama–French five-factor alphas (FF5) of a spread of a small quintile and a large quintile portfolio (using equal breakpoints). In columns (1)–(6), we employ factors by applying approximate NYSE breakpoints. In columns (7) and (8), we employ factors by applying equal breakpoints. All returns are adjusted for trading cost by using the transaction cost measure of Lesmond et al. (1999). We report heteroscedasticity and autocorrelation robust t-statistics according to Newey and West (1987) with three lags for the correction of autocorrelation in parenthesis. t-statistics refer to the null that the alphas are zero. Alphas are in percent per month and are denominated in domestic currency. We use the following time periods: 07/1991–02/2018: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Singapore, Spain, Sweden, Switzerland, U.K., USA; 07/2000–02/2018: Hong Kong; 07/1993–02/2018: Norway; 10/1995–02/2018: Poland; 07/2006–02/2018: Turkey the decile spread (with equal breakpoints); and for the USA, we detect positive and significant alphas for the decile spread with NYSE breakpoint in case of the five-factor model and for the decile spread with equal breakpoints for both factor models.

In sum, we find evidence that 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 is not exploitable by an active investment strategy. We observe similar patterns for the long-short strategy with the largest/smallest 20%. However, we observe some exceptions, most notably for the USA. Nevertheless, the large premiums documented in Sect. 3.1 are substantially diminished when accounting for transaction costs.

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, country-level common risk factors and portfolios. With this paper, we aim to make a step toward overcoming this obstacle. Specifically, we provide 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 US, 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 indexes with well-known representative stock market indexes are very high.

Moreover, we show that an extreme size premium exists in several individual countries. When accounting for trading costs, we find that these size premiums are substantially diminished and indeed are not realizable in most countries. Thus, seemingly large profits from trading on an anomaly can quickly evaporate when transaction costs are considered. This finding is most likely not just confined to size but may also extend to other anomalies documented in the literature. Therefore, we recommend to include such transaction cost analyses as part of the standard toolkit in empirical asset pricing research.

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A Appendix

A.1 Transaction cost estimation

This section explains the trading cost measure employed in Sect. 3.2 in greater detail.

Lesmond et al. (1999) propose a trading costs measure which is based on daily data. They assume that informed trading occurs on nonzero trading days and zero trading days indicate the absence of informed trading (Goyenko et al. 2009).[17]

Lesmond et al. (1999) propose a limited dependent variable (LDV) model as follows. First, they model the true (unobserved) returns for each firm j, R^*_{jt} as a linear function of the market returns R_{mt}:

$$R^*_{jt} = \beta_j R_{mt} + \varepsilon_{jt}, \tag{A.1}$$

where β_j denotes the market beta for each firm, and ε_{jt} an error term with zero expectation and a constant variance σ_j^2.

Second, they distinguish three cases to relate the measured returns R_{jt} to the true returns:

$$\begin{array}{ll} R_{jt} = R^*_{jt} - \alpha_{1j} & \text{if } R^*_{jt} < \alpha_{1j} \\ R_{jt} = 0 & \text{if } \alpha_{1j} < R^*_{jt} < \alpha_{2j} \\ R_{jt} = R^*_{jt} - \alpha_{2j} & \text{if } R^*_{jt} > \alpha_{2j}. \end{array} \tag{A.2}$$

Therefore, a nonzero return is only observed if either the true return is smaller than the threshold for negative information α_{1j} or bigger than the threshold for positive information α_{2j}. To obtain estimates for this model, one has to maximize the following log-likelihood function:[18]

$$\begin{aligned} \ln \mathcal{L} = &- \sum_{R_{jt}<0} \ln(2\pi\sigma_j^2)/2 - \sum_{R_{jt}<0} \frac{1}{2\sigma_j^2}(R_{jt} + \alpha_{1j} - \beta_j \cdot R_{mt})^2 \\ &- \sum_{R_{jt}>0} \ln(2\pi\sigma_j^2)/2 - \sum_{R_{jt}>0} \frac{1}{2\sigma_j^2}(R_{jt} + \alpha_{2j} - \beta_j \cdot R_{mt})^2 \\ &+ \sum_{R_{jt}=0} \ln\left(\Phi\left(\frac{\alpha_{2j} - \beta_j \cdot R_{mt}}{\sigma_j}\right) - \Phi\left(\frac{\alpha_{1j} - \beta_j \cdot R_{mt}}{\sigma_j}\right)\right). \end{aligned} \tag{A.3}$$

Here, Φ denotes the cumulative distribution function of the normal distribution. The parameters are estimated by maximizing the log-likelihood function in Eq. (A.3). We impose the following condition: $\alpha_{1j} < 0$; $\alpha_{2j} > 0$ and $\sigma_j > 0$. Note that the three different regions used in this expression are different than in Lesmond et al. (1999). Whereas in the original paper this regions are selected based on the market returns,

[17] We correct the observed daily zero returns as reported by TRD following Appendix A of Lesmond et al. (1999) to obtain effective zero returns.

[18] For further details see Lesmond et al. (1999).

we select these three regions based on the firm returns, as suggested by Goyenko et al. (2009).

To estimate trading costs, we use half of the estimated round-trip trading costs for each trade: $\frac{\alpha_{2j}-\alpha_{1j}}{2}$.

We estimate the LDV model for all stocks available on the daily TRD files. We use at least four years of daily observations to obtain a trading cost measure for each year. In addition to the daily observations of the year for which the trading costs are estimated, we use all daily observations of the 2 years before and after that year. Like suggested by Lesmond et al. (1999), we use the EW market return as a market return proxy. We assume that trading costs incur whenever a stock enters or leaves a portfolio.

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