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The Smallest Firm Effect: an International Study

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Abstract

Using a carefully screened and filtered international data base with a wide coverage across countries and size classes, this paper identifies and documents a post-1980s size effect which is persistent, not picked up by a Fama-French-style SMB, and largely due to the smallest-decile stocks. We test for potential explanations (such as market risk, infrequent trading, financial distress risk, missing book-values, momentum, liquidity risk, changing business conditions, January effect, exchange risk, time-varying risk loadings and dividend yield effects), but none can quite explain the international size effect, whether separately or jointly. Fully identifying the missing risk factor is beyond the scope of this paper but we do find that dividend yield shows up as a significant characteristic in the cross-section of risk-adjusted returns, even after controlling for time-varying risk loadings linearly related to dividend yield. When we construct two ad-hoc risk factors that jointly capture the documented size effect, and then correlate these factors with characteristics-based portfolios, we likewise find that especially dividend yield seems to play an important role in the missing risk factor. More generally, this paper revives the debate on the small-firm effect and, we hope, will stimulate further research on a class of stocks that are too interesting to ignore.

Keywords: forex, exposure, anomaly, Fama, French, dividend yield, liquidity, missing factor, size effect, small firm.
JEL-codes: C13, C22, G11, G12.

The Smallest Firm Effect: an International Study

Introduction and summary

Since the late 1990s, research on the size effect has been characterized by two developments that constitute a remarkable paradox (Dijk, 2011). On the one hand, theoretical models have emerged in which the size effect arises endogenously (Berk *et al.*, 1999; Gomes *et al.*, 2003; Carlson *et al.*, 2004). Simultaneously, however, the more recent empirical studies have raised doubt about the robustness of the size effect as of the early 1980s, a development that has brought a virtual halt to empirical research on the topic.

Perhaps the new consensus about the demise of the small-firm effect was premature, though. First, stock returns being very noisy and standard errors around estimates of the size premium large, it is not easy to tell whether the size effect is larger or smaller than it used to be. Second, international studies have often differed substantially in longitudinal and cross-sectional coverage, so that it is difficult to obtain a clear insight from alternative data. Third, while most of the U.S.-based evidence does rely on the same superb-quality database, CRSP, this source does not cover OTC stocks and therefore may miss part of the action. Compounding this, researchers have often actively filtered out the smaller firms present in their data base, even though Banz's (1981) evidence suggests that the size effect is not linear in the size ranking and is most pronounced for the smallest firms. It is true that the micro-cap stocks often suffer from severe data problems, and that is difficult and time-consuming to distinguish genuine returns from errors. Still, careful screening and filtering of the data[1] may be a better solution than either blindly trusting the data or removing all smallest-stock returns *a priori*. Thus, while we still ignore the absolutely tiny firms and the penny stocks, we nevertheless use a lower hurdle than other studies and, therefore, study a wider spectrum even for the U.S.; and we add international data (39 countries), all for the same period (1980-2009) and subject to the same filters.

Besides documenting the size effect in a wide-coverage and clean international data base, we also systematically test potential explanations of the size effect. We find that the size effect is still very much present in the post-1980s period and that it is largely confined to the smallest-decile stocks. The potential explanations for the size effect that we tested are: market risk, infrequent trading, financial distress risk, missing book-values, momentum, liquidity risk,

[1] See Ince and Porter (2006) for a review of many of the problems in the Reuters/Datastream files.

changing business conditions, the January effect, exchange risks, time-varying risk loadings and dividend yield effects. We find that these effects do not subsume the size effect, neither separately nor jointly. Fully identifying the missing risk factor is beyond the scope of this paper but we do find that dividend yield shows up as a significant characteristic in the cross-section of risk-adjusted returns, even after controlling for time-varying risk loadings linearly related to dividend yield. In an attempt to get some further insight into the missing risk factor, we construct two ad hoc risk factors that do capture the international size effect jointly, and we correlate them with characteristic-based portfolios. We find again that especially dividend yield seems to play an important role in the missing factor.

The remainder of the paper is organized as follows. We briefly review the literature on the small size effect in Section 1. In Section 2 we describe the dataset and the screening and filtering procedures. Extensive descriptive statistics of the sample and the portfolios follow in Section 3. In Section 4 we systematically investigate the potential size premium explanations and test them formally, both separately and jointly. Section 5 has a closer look at the missing factor. Section 6 concludes.

1 Literature review

In this section we briefly review the existing evidence on the size effect and the potential explanations of the size premium.[2]

1.1 Early U.S. evidence

Banz (1981) provided the first systematic evidence of a size effect in U.S. stock returns. Studying all common stocks listed on the NYSE between 1936 and 1975, Banz reports that stocks in the quintile portfolio with the smallest market capitalization earn a risk-adjusted return that is 0.40% per month higher than the remaining firms. Fama-MacBeth (1973) regressions show a negative and significant relation between returns and market value. However, Banz finds 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. Despite various important contributions in the decade after the original work by Banz,[3] research on the size effect really took off after the appearance of Fama and French (1992). They examine the size and book-to-market anomalies uncovered by earlier studies and demonstrate that the empirical

[2] For an excellent review, see Dijk (2011), on which we occasionally draw?

[3] For example, Reinganum, 1981; Brown, Kleidon, and Marsh, 1983; Keim, 1983; Lamoureux and Sanger, 1989

shortcomings of the Capital Asset Pricing Model (CAPM) are too important to be ignored. They find that beta does not help to explain the cross-section of returns (the "beta is dead" conjecture) but both size and book-to-market equity have significant explanatory power.

1.2 Early international evidence

Since the late 1980s, a large number of studies have examined the magnitude of the size effect in an international context.[4] These studies are interesting because the strength of the size effect might depend on market characteristics such as the trading mechanism, the type of investors and market efficiency in general. Any finding that the size effect exists in other markets too and in different time periods would provide a strong argument against data mining concerns (Lo and McKinlay, 1990; Black, 1993). The international evidence on the size premium seems, in fact, remarkably consistent: small firms appear to outperform large firms in the majority of the countries investigated, including European and emerging markets. However, there are a number of important caveats that may make the reported international evidence on the size effect less convincing and perhaps even inconclusive. First, it is hard to judge whether small firms also outperform large firms on a risk-adjusted basis because many international studies make no attempt at all to adjust for risk. Second, the sample composition of several studies raises doubts about the reliability of the results. Papers that study ten years of data or less, cover fewer than 100 securities, or sort stocks into three portfolios or less are unlikely to yield a reliable estimate of the size premium.

Lastly, there is the issue of whether the size of a firm should be measured relative to the average size of firms in its country. It is true that, for some countries, the adoption of absolute firm size makes it hard to distinguish the size effect in stock returns from a country effect; but scaling the size of an individual firm by the country's mean firm ignores the fact that the largest firms from a small country might be relatively small in a global context. Locally-large but globally-small firms should still earn relatively high returns if the size effect holds and markets are integrated internationally. In addition, if there is a logic for scaling by country, the same might then be claimed for sectors—Software & Computer Services firms, for example, are typically small, for instance; but scaling by both country and sector is difficult. Lastly, any

[4] Australia: Beedles (1992); Belgium: Hawawini, Michel, and Corhay (1989); Canada: Elfakhani, Lockwood, and Zaher (1998); China: Drew, Naughton, and Veeraraghavan (2003); Emerging markets: Rouwenhorst (1999); Europe: Annaert, Van Holle, Crombez, and Spinel (2002); Finland: Wahlroos and Berglund (1986); France: Louvet and Taramasco (1991); Germany: Stehle (1997); Ireland: Coghlan (1988); Japan: Chan, Hamao, and Lakonishok (1991); Korea: Kim, Chung, and Pyun (1992); Mexico: Herrera and Lockwood (1994); Netherlands: Doeswijk (1997); New Zealand: Gillan (1990); Singapore: Wong, Neoh, and Lee (1990); Spain: Rubio (1986); Switzerland: Cornioley and Pasquier (1991); Taiwan: Ma and Shaw (1990); Turkey: Aksu and Onder (2003); United Kingdom: Strong and Xu (1995).

such scaling diminishes the dispersion in the explanatory variable, which reduces the power of the test. Empirically, there is no consensus. On the one hand, Annaert *et al.* (2002) and Rouwenhorst (1999) can only report a substantial size effect if stocks are sorted on the basis of absolute firm size. On the other hand, Heston *et al.* (1999) and Barry *et al.* (2002) only find evidence of a size effect when they measure size relative to the local market.

1.3 Evidence on the post-1980s size effect

There is evidence indicating that the U.S. size effect disappeared after the early 1980s. Eleswarapu and Reinganum (1993), Dichev (1998), Chan, Karceski, and Lakonishok (2000), Horowitz, Loughran, and Savin (2000), and Amihud (2002) find no size premium over their sample periods of 1980-1990, 1980-1995, 1984-1998, 1979-1995, and 1980-1997, respectively. Dimson and Marsh (1999) report that small stocks underperformed large stocks by 2.4% between 1983 and 1997. Also Hirshleifer (2001) contends that the size effect vanished after 1983. Schwert (2003) suggests that the size anomaly disappeared because practitioners began to use investment vehicles that tried to exploit the anomaly around the time of its discovery. There is some indication that also in non-U.S. markets the size premium varies across different time periods. Dimson and Marsh (1999) show that the size premium reversed in the U.K.: the size premium was 5.9% per year over the period 1955-1988, while it amounted to –5.6% over the period 1989-1997. Dimson, Marsh, and Staunton (2002) found in 18 out of the 19 investigated countries that the size effect reversed in the period after which an academic study on the size effect appeared in that country.

1.4 Potential explanations of the small firm effect

The firm size effect is often called an anomaly because there is no widely accepted theoretical reason why size per se should have any power explaining the cross-sectional differences in asset returns, after controlling for risk. The empirical finding that size has explanatory power suggests that it is proxying for risks that were either ignored or not measured properly. This section provides an overview of earlier attempts to explain the size effect in one of these ways.

1.4.1 Non-synchronous trading

Roll (1977) conjectures that the size effect may be a statistical artifact of improperly measured betas. Scholes and Williams (1977) and Dimson (1979) had already pointed out that, when the underlying security trades infrequently, non-synchronous trading biases the estimated beta—downward for infrequently traded shares and upward for frequently traded shares. Roll maintains that since the shares of small firms are generally the most infrequently traded and the shares of large firms are the most frequently traded, the betas for small firms are biased downward while the betas of large firms are biased upward. Thus, estimation of abnormal returns using risk estimates that are not adjusted for trading infrequency may yield the observed size effect. Dimson (1979) estimates market sensitivities (betas) in the presence of thin trading via a multiple regression that includes leads and lags of the market return.[5] Also Cohen *et al.* (1983) and Scholes and Williams (1977) provide adjustments for non-synchronous trading.

1.4.2 Financial distress risks

One of the central themes of Fama and French (1993) is that if assets are priced rationally, variables that are related to average returns, such as size and book-to-market equity, must proxy for sensitivity to common risk factors in returns. They give direct evidence on this issue by constructing mimicking portfolios for the underlying risk factors related to size (SMB) and book-to-market (HML). They find that the market, SMB, and HML portfolios capture a substantial part of the time-series variation in the returns on 25 stock portfolios formed on size and book-to-market over the period 1963-1991. Fama and French (1996) show that the three-factor model also captures the returns on portfolios formed on the basis of other anomalies. They argue that the empirical success of the three-factor model indicates that it is an equilibrium pricing model, a three-factor version of Merton's (1973) intertemporal CAPM or Ross's (1976) arbitrage pricing theory.

Other studies address the issue what state variables produce variation in returns related to size and book-to-market. Fama and French (1995, 1996), Chan *et al.* (1985), Chan and Chen (1991), Vassalou and Xing (2004), Petkova (2006), Malkiel and Xu (1997, 2004) and Boons, De Roon and Szymanowska (2010) relate the size effect to, respectively, relative distress, changing economic environment, fallen angels, default risk, innovations in variables that describe the investment opportunity, idiosyncratic risk, and commodity prices (as state variables, not as deflators).

Some, including Dichev (1998) and Campbell *et al.* (2008), question the conclusion that the size effect can be explained by relative distress. Also Daniel and Titman (1997) question the interpretation that size proxies for a firm's exposure to an underlying risk, arguing that firm characteristics, not factor loadings on the SMB and HML portfolios, determine expected returns. Within portfolios formed on size, there is essentially no relation between returns and loadings on the SMB factor, for instance. Expected stock returns thus seem to be related to

[5]The leading market return is needed because part of today's true market return will show up tomorrow only because some stocks do not trade today, while the lagged market is needed because for a stock that did not trade yesterday, today's reported return is partly explained by yesterday's true market return.

firm characteristics for reasons that may have nothing to do with the covariance structure of returns. Berk, Green, and Naik (1999) adress the critique that the risk-based explanations of the size effect are not grounded in economic theory. These papers analyze firm-level investment decisions in models in which the relation between firm size and stock returns arises endogenously. Theoretical papers that build on Berk *et al.* include Gomes, Kogan, and Zhang (2003) and Carlson, Fisher, and Giammarino (2004).

1.4.3 Liquidity

Liquidity is generally described as the ability to trade large quantities quickly at low cost with little price impact. Empirical studies have employed several liquidity measures. Examples are the bid-ask spread (e.g. Amihud and Mendelson, 1986); turnover (e.g. Datar et al., 1998); the proportion of zero returns (e.g. Lesmond *et al.*, 1999); the measures of Amihud (2002) and Pastor and Stambaugh (2003) that employ the concept of price impact to capture the price reaction to trading volume; and the measure of Liu (2006) which is the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months.

Liquidity has been shown to affect the cross-sectional differences of asset returns through two different channels, notably either as a characteristic or as a risk factor (i.e. a priced state variable).[6] But liquidity also seems to be related to the size effect. Amihud and Mendelson (1986), for instance, conclude that liquidity subsumes the size effect in returns from equities. However, Eleswarapu and Reinganum (1993) criticize Amihud and Mendelson for excluding very small stocks from their sample. In their much broader dataset, cross-sectional variation in the bid-ask spread cannot fully explain the size effect. Amihud (2002) finds that the returns on small firms are sensitive to time-series variation in market liquidity. Variation in the size premium may thus be related to time-variation in the price of liquidity risk. Still, changes in market liquidity account for only a minor part of the time-series variation in returns. He also finds that both size and liquidity are significant in Fama-MacBeth (FM) regressions, which suggests that the liquidity variable does not capture the size effect completely. Pastor and Stambaugh (2003) find that portfolios of small firms have the highest loadings on the liquidity factor but, they stress, the relation between liquidity risk and firm size is not straightforward. They do not investigate whether size remains a significant determinant of expected returns after correcting for liquidity risk. Acharya and Pedersen's (2005) cross-sectional tests show that augmenting the CAPM with a liquidity factor improves the explanatory power, and that

[6] Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Amihud, (2002) document the first channel; the second is described by Pastor and Stambaugh (2003), Acharya and Pedersen, (2005), Liu (2006), Sadka (2006), Watanabe and Watanabe (2008).

the liquidity risk premia are economically significant. Small stocks have lower average liquidity and higher exposures to various liquidity risk factors. The liquidity risk factors improve the fit for portfolios of small stocks, but Acharya and Pedersen do not examine whether liquidity risk subsumes the size effect. Liu (2006) finds, in the U.S. market, that a two-factor model (market and liquidity) subsumes well-documented anomalies such as the size effect. Recently, Lee (2010) tested Acharya and Pedersen's state-variable model on a global level instead of only on the U.S. market, and found evidence that liquidity risks are priced independently of market risk in international financial markets.[7]

1.4.4 The business cycle

When characteristics of the opportunity set, such as risk premiums, change over time, models of intertemporal asset pricing suggest that assets' expected returns may be related to the sensitivities of their returns to changes in those characteristics (Merton, 1973; Ross, 1976; Cox, Ingersoll and Ross, 1985; Chen, Roll and Ross, 1986). Chan, Chen and Hsieh (1985) show that a substantial portion of the firm size effect seems to be related to the exposure to the changing risk premium. They use the difference in return between a portfolio of low-grade bonds and a portfolio of long-term government bonds as a proxy for the changing risk premium. Their hypothesis is that the risk premium may change as a result of changing business conditions. In this view, smaller firms are riskier than larger firms (and therefore have higher expected returns) because they are more sensitive to economic expansions and contractions. This is consistent with the scenario that, during business contractions, marginal or, often, small firms suffer a relatively high rate of failure and large negative returns, which risk is in turn reflected in higher average returns to the bearer.

Another hypothesis relates to the different timing of the influence of the market premium and the changing risk premium on the returns of smaller firms. The market premium is often regarded as an indicator of future economic conditions. In case of an economic upturn, marginal firms do not tend to revive until the actual growth rate of the economy is known. In case of an economic downturn, in contrast, marginal firms are often the first to react to any increase in the uncertainty of the economy. Therefore, the movements of these firms may be less coincident with the movement of a general market index, but more with the changing risk premium which is regarded as an indicator of the business cycle.

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[7] The model of Acharya and Pedersen (2005) is often referred to as the liquidity-adjusted capital asset pricing model, whereas the model of Liu (2006) is often called the liquidity-augmented capital asset pricing model.

1.4.5 The January effect

Keim (1983) finds that a large part of the differential risk-adjusted returns to small firms' stocks occurs in the first week of January. Other studies include Brown, Kleidon and Marsh (1983), Lamoureux and Sanger (1989) and Daniel and Titman (1997). Many researchers explore the tax-loss selling hypothesis to explain the January effect. Toward the end of the year, individual investors have a tax incentive to sell stocks that declined in price during the year, realized capital losses being tax-deductible. After the turn of the year, the selling pressure disappears and prices recover. This effect can be especially important for portfolios of small stocks, since these are biased toward shares that have experienced large price declines.

But when Thaler (1987) surveys early research on the January effect and the tax-loss selling hypothesis, international evidence shows that taxes are not the entire explanation. A second explanation for the January effect, then, is provided by the window-dressing hypothesis. To present respectable-looking portfolio holdings, institutional investors have an incentive to buy winners (or other low-risk stocks) and sell losers at the end of the year. Early in January, they rebalance their portfolios in favor of more speculative securities, thus inducing the same price-pressure patterns as those predicted by the tax-loss selling argument (Ritter and Chopra, 1989; Sias and Starks, 1997; Poterba and Weisbenner, 2001; Ortiz, Ramirez and Vicente 2011).

Information patterns can provide a third explanation for the January effect. For firms with year-end fiscal closings the month of January marks a period of increased uncertainty and anticipation due to the impending release of important information. In addition, the gradual dissemination of this information during January may have a greater impact on the prices of small firms relative to large firms for which the gathering and processing of information by investors is a less costly process (Rozeff and Kinney, 1976).[8]

1.4.6 Exchange risk

The CAPM, with its one single world-market factor, may be inadequate to price stocks in an international setting even if capital markets are well integrated, both organizationally and informationally. Notably, real exchange risk means that real returns depend on the investor's country of residence. To adjust the CAPM for the fact that investors from different countries think in different real units, exchange-rate factors must be added (Sercu, 1980), and exposure to currencies must be priced.

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[8]Sun and Tong (2010), however, find no trace of seasonals in aggregate market risk, so they hypothesize that relative risk aversion is seasonal, instead. This hypothesis is also invoked by Liu and Sercu (2010) to explain the shifting relation between consumption growth and interest rates around the turn of the year.

Although we introduce exchange-rate factors here mainly on general *a priori* grounds, there could still be a link with the size effect: small firms might be more sensitive to exchange risk because they are less mature and less diversified, similarly to their exposure to business cycles. They may also have less elaborate hedging policies.

1.4.7 Dividend yield effects

The tax penalty generally associated with dividends relative to capital gains has led to the hypothesis that anticipated dividend yields and expected returns are positively related. Blume (1980), however, reports a U-shaped relation between returns adjusted for beta risk and dividend yield. Summers (1982) argues the U-shape could arise if zero-dividend firms are riskier than the lowest-yielding corporations. This argument crystallizes in Keim (1985) who documents that small firms tend to concentrate in the zero- and high-yield portfolios, while large firms are overrepresented in the portfolios of stocks with low but positive yields. The size effect is then expected to induce this U-shaped relation between returns and dividend yields. Keim also shows that the January seasonal in the size effect manifests itself as a January seasonal in the U-shaped yield effect. However, Keim formally shows that the dividend yield still has marginal explanatory power even when the test controls for size and the January seasonal. Related work by Christie (1990) reports that zero-dividend firms earn negative average excess returns relative to firms of similar size. Christie explains this by dividend-expectation effects, i.e. the market's expectation that cash dividends will be introduced or resumed. Nevertheless this evidence demonstrates the distinct effect of zero-dividend yield.

In the above, the evidence is about the ability of dividend yield to explain the cross-section of stock returns as a characteristic, not a risk factor. The fact that this 'non-risk' firm characteristic is a significant explanator of the risk-adjusted returns implies that the risk adjustment is incomplete, or that the characteristic is a proxy for the loading on some priced risk factor that is not included in the analysis. Chen *et al.* (1990), however, show that dividend yield is related to expected returns not just cross-sectionally but also over time. This opens up the possibility that the explanatory power of dividend yield may be caused by the practice of estimating risk measures as constants where in fact the true risk measures change through time—for instance, in line with the dividend yield. Chen *et al.* find indeed no reliable cross-sectional relation anymore between dividend yield and risk-adjusted expectations when the risk measures are linearly related to dividend yield.

This fits into the more general observation that the CAPM is a static model and that many empirical tests assume that betas are constant over time. In reality, however, the relative risk of a firm's cash flows and market value is likely to fluctuate over time. Conditional versions of the CAPM take this variability into account by making expected returns conditional on the information available to investors at a given point in time (see e.g. Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001; Santos and Veronesi, 2006; Daniel and Titman, 2005). Lewellen and Nagel (2006) investigate whether their conditional CAPM can explain asset pricing anomalies. They find that although betas vary considerably over time, they do not vary enough to explain known anomalies. Ferson and Schadt (1996) consider time-varying betas in the context of mutual funds. It is true that market timing is more of an issue with actively managed mutual funds and less with passive portfolios based on some firm characteristic such as size. However, it may still be possible that passive portfolio rebalancing induces time-variation in the betas which may be linked to dividend yield.

1.4.8 Information asymmetries

The size effect can also originate from incomplete information about small firms: analyst following and press coverage are positively related to size. Merton's (1987) investor recognition hypothesis predicts that less well-known stocks of firms with smaller investor bases have higher expected returns. Banz (1981) also conjectures that many investors do not want to hold small stocks because of insufficient information, leading to higher required returns on these stocks. Hou and Moskowitz (2005) offer an empirical analysis of the influence of investor recognition on the size effect. As a broad measure for market frictions, the authors propose the average delay with which a firm's stock price reacts to information. Price delay has a significant impact on the cross-section of U.S.stock returns over the period 1963-2001, and captures a substantial part of the size effect. Hou and Moskowitz argue that the results are most consistent with frictions associated with investor recognition.

1.4.9 Data errors, extreme returns and delisting bias

Among empirical researchers, it is generally accepted that the probability of data errors is negatively related to firm size, especially for the tiny, illiquid and penny stocks. Familiarly, errors in prices spuriously increase the mean return.[9] Knez and Ready (1997) show that the size effect is driven by the extreme 1% of the observations. Hypothesizing that the extreme observations are errors rather than genuine outliers, they analyze the Fama and French (1992) data with a robust regression technique, least trimmed squares, which trims a proportion of the observations and fits the remaining observations using least squares. When Knez and Ready trim the extreme 1% of the observations, the FM regressions no longer yield a significantly

[9] Denoting the percentage error in the reported time-t price by e, the average return straddling a data error e on date t equals $(1/2)\left(\frac{P_t(1+e)}{P_{t-1}} + \frac{P_{t+1}}{P_t(1+e)}\right)$. Regardless of the sign of e, the spurious percentage drop is smaller than the spurious rise. The expected net effect is $[1 + \mathrm{E}(r)]E[1/(1 + e)] \approx [1 + \mathrm{E}(r)][1 + \mathrm{var}(e)] - 1$.

negative coefficient on firm size; they actually find a positive coefficient instead. Equally interesting, in their analysis most small firms underperform big firms, not the other way around. Thus, the size effect seems to a mean-versus-median story: a tiny fraction of the small firms do extremely well, like the 'turtle eggs' effect. Fama and French (2007) examine the migration of firms across size portfolios and likewise conclude that the size premium stems almost entirely from small stocks that earn extreme positive returns on their way out of the lowest percentiles.

A different type of error may stem from the missing last return in case of a delisting. Shumway and Warther (1999) investigate the implications of the delisting bias in Nasdaq data. They collect over-the-counter data on delisting returns and propose using a delisting return of -55% for the delisted stocks with missing data. They re-examine the size effect based on Nasdaq data over the period 1972-1995 and find no evidence that there ever was a size effect on Nasdaq.

This concludes our review of the size effect. In Section 4 we systematically test these potential explanations, separately and jointly, on our international research dataset. But first we describe our dataset (Section 2) and we provide extensive descriptive statistics on the individual stocks and the portfolios (Section 3).

2 Data selection

Earlier studies have used Thomson Reuters Datastream (TRD) because of its coverage in terms of number of markets,[10] or its intra-country coverage[11] which nowadays often encompasses all stocks traded within a national market. We use TRD to do both, i.e. creating an equity dataset that offers maximal coverage within and across countries.

From January 1980 till May 2009, monthly dollar returns are calculated using a monthly dollar total return index, which is adjusted for stock splits and dividend payments, for all available stocks from 39 countries selected on the basis of data availability and coverage within and across regions: North America (Canada, United States), Latin America (Argentina, Brazil, Chile, Colombia, Mexico, Peru), Japan, Asia-ex-Japan (China, Hong Kong, India, Indonesia, Malaysia, Philippines, Singapore, South Korea, Taiwan, Thailand), Euro-in countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Greece), Euro-out countries (Denmark, Norway, Sweden, UK, Switzerland), Australasia

[10] See e.g. Griffin *et al.*, 2003; Naranjo and Porter, 2005; Griffin, 2002; Kaniel, Li, and Starks, 2005; Bekaert *et al.*, 2006; Lee, 2010)

[11] See e.g. Clare and Priestley, 1998, for Malaysia; Brooks *et al.*, 2001, for Australia; Pinfold *et al.*, 2001, for New Zealand; Hiller and Marshall, 2002, for the United Kingdom; Lau *et al.*, 2002, for Singapore and Malaysia.

(Australia, New Zealand) and South-Africa.

The dataset contains the ups and downs of the post-1999 period and offers sufficiently long series even for emerging markets (EMs), as many start in the late 1980s and 1990s. The use of monthly dollar returns is common in this kind of research. The monthly frequency should offer a sufficient number of observations for a reasonable power in the regression tests without picking up excessive microstructure-induced autocorrelation in the returns. The dollar is the most common numéraire, in this literature. Exchange rates are also from TRD, while the U.S. one-month T-Bill was downloaded from Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

An important caveat when including TRD's 'all (currently) available stocks' list is that especially the smallest stocks may suffer from significant liquidity constraints, survivorship bias and other data problems inherent in TRD. Ince and Porter (2006) document these important issues of coverage, classification, and data integrity and find that naive use of TRD can have a large impact on economic inferences. But they also show that, for the U.S. market, inferences drawn from TRD data after careful screening and filtering, are similar to those drawn from CRSP data. Based on the filters developed using U.S. TRD data, they provide guidelines for screening international TRD data. The screens we apply to the international TRD data are in line with, and occasionally go further than, the guidelines proposed in Ince and Porter (2006).

We extract the stock list from the TRD 'Research' and 'Dead' lists for each country and then screen and filter for undesired assets. More specifically, we delete dual listings within and across exchanges (ADRs, GDRs, identical shares), preferred shares, warrants, certificates, shares from the same company but with different voting rights, error shares (shares with no name, one-month shares), shares that duplicate information on individual companies i.e. the sectors[12] Real Estate Investment Trusts (REITs), Equity Investment Instruments (investment trust and venture capital trusts) and Nonequity Investment Instruments (open-ended investment companies and funds, unit trusts, ETFs, currency funds and split capital trusts).

For the 'dead' stocks, TRD leaves the last recorded stock price in its system which causes a series of spurious zero-returns (for U.S.-dominated stocks) or a series of spot currency returns (for non-U.S. dominated stocks) after the end date. We therefore cut off the return series of the resulting stock list based on the stock's start and end date. It is not clear what the dead stock's last dollar return is. In case of bankruptcy, the dead stock's last dollar return lies between

[12]TRD uses the Industry Classification Benchmark (ICB) classification model for equities (http://www.icbenchmark.com/docs/Structure_Defs_English.pdf). This industry structure contains 4 levels namely 10 industries, 19 super sectors, 41 sectors and 114 subsector. We used the classification of 41 sectors as this offers a level of detail that is comparable to the country classification (39 countries).

zero and -100%. In case of a take-over or merger, there is no upper bound. We investigated the influence of the dead stock's last dollar return by computing three risk factors (based on size, book-to-market and momentum) for two datasets, one where the dead stock's last dollar return is set equal to -100% and the other where it is set at 0%. The differences between the risk factor returns for both datasets were negligibly tiny. This way we can reasonably assume that the delisting bias (Shumway and Warther, 1999) is not an important issue in our dataset. Given the uncertainty about the dead stock's last dollar return and its negligibly tiny influence, we decided not to impose any arbitrary dead stock's last dollar return.

We then eliminate the return observations of tiny, illiquid and penny stocks which are reasonably more likely to contain data errors. Penny stocks are often fallen angels (Chan and Chen, 1991) which are highly speculative. Tiny companies have also limited liquidity, can be subject to high price pressure or price manipulation, and often represent too little value to warrant attention. For these reasons we removed price formation of a stock with a market capitalization below $10,000,000 or a monthly trading volume smaller than $100,000 or a price smaller than $1. Whenever trading volume information is not available, we consider an unchanged monthly local price as a sign that in that month there was no meaningful trading volume; in that case, the month-end price is deemed to be unreliable, meaning that both returns based on this price are eliminated. Lastly, we eliminate all returns corresponding to a negative book-to-market value.

After applying these automated screens we visually screen the return plots for extreme-return errors that can be influential for regression results. The high-return errors that slipped through the automated filters are caused by, for example, decimal-sign shifting (a huge price rise preceding or following a similarly huge drop); anomalously low first price of a series (probably theoretical or illiquid); high reported returns not corresponding to a similar change in the market capitalization or price or not mirroring a huge dividend payout; data reported before the actual introduction date or after the actual delisting date; obvious typos; wrongly handled equity offerings. We kept on eliminating these suspect high returns until the first one-hundred highest remaining returns seemed acceptable. This way we minimize the possibility of anomalously blowing up the 'turtle eggs' effect (Knez and Ready, 1997) and causing the size premium to be due to faulty extreme returns.

Eventually, we end up with roughly 4,000 ongoing stocks during the first years of the 1980s growing to more than 18,000 in the 2nd half of 2007. On average, the dataset contains more than 10,000 ongoing stocks over a period of almost 30 years or, more precisely, 352 months. The stock list consists of roughly 55% active stocks and 45% delisted stocks. This illustates the potential importance of survivorship bias if delisted stocks are ignored in long-term international studies. The wide scope of the dataset, both in the number of ongoing stocks and years, adds to the reliability of the results. Data on firm characteristics is always synchronized with the screened and filtered return data. This is important to have reliable characteristics-based portfolio returns.

3 Descriptive statistics

3.1 Distribution of individual stocks across countries, sectors, and size classes

An extensive description of the distribution of stocks across countries, sectors, and size classes is provided as an Appendix. Of the more salient points, useful for the results, we just mention the following: (i) the four biggest countries in terms of the number of stocks listed are the U.S., Japan, the U.K., and Korea, with Japan strongly biased towards big stocks while Korea and the U.S. (with its OTC market) are biased towards small ones. (ii) Many countries represent less than 1% each of the aggregate cap, but as a group they still add more value than e.g. the U.K.. (iii) EMs have higher volatilities and returns than developed markets (DMs), but there is no systematic difference in terms of Sharpe ratios. (iv) Small firms often come from DMs; some EMs (like the Philippines and Singapore, admittedly a border case) actually have very few of them.

3.2 Portfolios

3.2.1 Portfolio formation

Throughout this paper portfolios are equally weighted, except for the market portfolio which is proxied by the value-weighted TRD World Market Index. While the portfolio-theory logic underlying the CAPM dictates value weighting as far as the market portfolio is concerned, there is no such theoretical basis for other portfolios such as characteristics-based portfolios or zero-investment mimicking portfolios. Empirically, value-weighting is often motivated by potential data problems with tiny, illiquid or penny stock. However, the dataset in this study is thoroughly screened and filtered for potential data problems especially related to those smallest firms.

Portfolios are rebalanced every month, unless stated differently. Lower-frequency rebalancing could reduce the power of the regression tests as firms may shift to another size class during one year. For reasons discussed in Section 1.2, size decile values are extracted from the global distribution without correction for country or sector size standards.

3.2.2 Size portfolio statistics

To study the international small firm effect we divide the pooled sample into ten size portfolios. Working with ten one-dimensionally sorted portfolios is common in this kind of research and should yield enough dispersion in size across portfolios to reliably estimate the size premium. In order to better understand the nature of the small firm effect we provide unconditional descriptive statistics on the ten size portfolios.

Figure 3 plots a time series of monthly returns, computed from a moving window of the twelve preceding months, for the smallest and biggest size portfolios as well as the market portfolio. The returns paths of the biggest size portfolio and the market portfolio are very close, as one expects given that the top decile stands for 80% of the market cap. The smallest size portfolio follows a roughly comparable path, except that it exhibits higher-beta characteristics: more pronounced ups and downs, and higher overall returns. Lastly, we note that the difference between the green and red line fluctuates over time which suggests that the size premium is time-varying. For example, during the ICT crisis (from 2001) the size premium was high whereas during the financial crisis (from 2008) the size premium was small.

The geographical and sectoral distribution of the smallest size portfolio compared to the pooled sample was already discussed in the Section 3.1. and the Appendix. From Figure 4 and 5 we again see that the smallest firm portfolio is more oriented to U.S. and Korean stocks and less to Japanese stocks compared to the pooled sample. The sectoral difference between the smallest-firm portfolio and the pooled sample is much smaller. Even though the vertical scales of Figure 4 and 5 differ, we can still see that the smallest-firm portfolio is slightly more oriented to Electronic & Electrical Equipment and Software & Computer Services.

Table 3 provides unconditional statistics for the size portfolios: the average monthly return, the standard deviation, the frequency of firm movements by portfolio and the frequency of firm leaving the sample, by portfolio. In the second column of Table 3 we see that the unconditional size effect is not linear in market value; the main effect occurs for the smallest firms while there is little difference in return between average-sized and large firms. The unadjusted size premium is huge for the smallest stocks with 2.23% per month. This drops to 0.41% for the second smallest portfolio to only 0.18% or less for the others. From the third and fourth column we see that the non-linear size premium is only marginally linked to differences in total risk measured by the standard deviation. We see again that the largest size portfolio most closely resembles the market portfolio.

Following Fama and French (2007) we also examine the migration of firms across size portfolios. Table 3 shows the migrations into the adjacent portfolio(s).[13] We see that the smaller size portfolios are less stable than the larger portfolios. In a randomly selected month, for example, 96% of the biggest firms can be expected to stay in the top size portfolio compared to only 79% for the smallest portfolio. A lot of the movements at the bottom is pure drop-out. Of the 21% that move out from decile 1, 12% actually disappear from the sample rather than moving into decile 2. Some of these exits are genuine delistings, but part of the attrition also reflects our screening rules. But exits are far from concentrated in decile 1, especially if one waits longer than one month. To show this, the last columns of Table 3 look at prior size-bucket membership given that there was an exit, again without making the distinction between the two possible reasons. We see that if a firm leaves the database, it is only slightly less likely that it used to be a large firm one, five or ten years before.

4 Testing the potential explanations of the small firm effect

In this section we empirically explore and formally test the potential explanations of the small firm effect—the risk factors potentially missing from the static CAPM—as reviewed in Section 1.4. Following Breeden (1979) and Fama and French (1996), we let mimicking portfolios replace the state variables in the intertemporal asset pricing model of Merton (1973). To test the ability of CAPM-augmenting risk factors to account for the size premium we mainly adopt the time-series regression approach of Black, Jensen and Scholes (1972).

4.1 Market risk and infrequent trading

To set the stage we test the ability of the standard CAPM to explain the size premium, before and after correcting for thin trading. Panel A of Table 5 shows that the standard CAPM cannot account for this size premium. We note that the beta-adjusted size effect is not linear in the size classification: the main effect occurs for the smallest firms, where the unexplained risk premium actually exceeds to the raw one (2.31% per month versus 2.23%).

To control for the problem of estimating beta due to non-synchronous trading, more likely occurring for the small stocks, Panel B also reports the coefficients of the Dimson-beta-adjusted CAPM with two leads and lags. The one-period lagged betas are larger for the smaller portfolios while the contemporaneous betas are positively correlated with size, telling us that smaller stocks react with a lag (or seem to, if the problem is just thin trading). Summing the betas per size portfolio so as to get their total market sensitivities, all total betas become close to

[13] Migrations to a bucket two or more positions away are so rare that they can be ignored.

unity. The resulting alphas are smaller but still significantly different from zero for the smaller portfolios and the adjusted R^2s do not improve. So, correcting the CAPM for non- synchronous trading yields betas close to unity and does somewhat shrink alphas but still cannot account for the performance of the smaller portfolios and the size premium.

4.2 FF Financial distress risk, missing book-values and momentum

The Fama-French (1993) model (FF) accounts, next to market risk, also for financial distress risk by adding two risk factors to the CAPM. One factor is based on size which is obviously related to the size premium. The other is based on the ratio of book over market value. From Table 6 we see that portfolios formed on high book-to-market values generate more return than low book-to-market portfolios. This is often referenced to as the distress premium. We also see that the smaller portfolios tend to be composed by higher book-to-market firms which makes the book-to-market based factor potentially relevant for explaining the size premium. Table 7 sums up the results for the FF model. From Panel A we see that the bigger the firm, the smaller its loadings on both size-related risk factors. Market betas all remain close to unity and the adjusted R^2s for the smaller portfolios are above 80%, much better than under the CAPM. Lastly, the risk-adjusted size premium drops to 1.31% per month (compared to 2.23% unadjusted), but it does remain significant. So while the FF model substantially improves the explanation of the size premium, it still cannot account for the performance of the smallest stocks. Relative to the CAPM, we now also see negative alphas. Notably, the FF model seems to over-adjust for size-related risk for the decile 2-to-5 smaller stocks.

The FF methodology requires the firm's book value to be known for inclusion in the SMB_t factor. Firms with missing book values are present in the size portfolios but not in the FF risk factors. So we test whether any bias is introduced by our filtering on missing book values. From Table 6 we see that missing accounting data are especially a problem for the smaller firms. On the other hand, we also note that these missing-book-value firms are performing worse than the other firms in their size portfolio, not better, and that the magnitude of this underperformance is rather similar across the size portfolios. This suggests that the missing-book-value firms are not behind the positive alpha for decile 1. We test this more formally by recomputing the size factors to include also the missing-book-value firms and see whether this generates alphas closer to zero.

The alternative FF factors, denoted by asterisking their standard acronyms, are constructed as follows. Necessarily, we abandon two-dimensional stratification and simply form two size portfolios containing, every month, the top-50% and lower-50% firms. For the HML_t^* factor we proceed likewise except for the 30% cut-off. The lack of two-dimensional sorting explains why the new factors now have a non-trivial positive correlation (0.30) rather than a slightly negative one (–0.10).

Panel B of Table 7 shows the new test results. Alphas, betas and loadings to the SMB_t^* factor remain virtually unchanged, but the loadings on the HML_t^* factor become insignificant and even negative for the smaller portfolios, a result that is probably reflecting the mild collinearity problem with this test than anything genuine. At any rate, the missing-book-value firms do not seem to be responsible for the size premium, and adjusting the FF factors muddles rather than clarifies the picture.

Missing-book-value firms may still be important because some other characteristic than size may be associated to them. Table 8 provides the geographical and sectoral distributions and proportions of the missing-book-value firms. We notice that the proportion of missing book values is similar across developed and emerging markets. The big countries are also responsible for most of the missing-book-value firms in the pooled sample.[14] At any rate, we do not notice any unusual pattern in the sectoral distribution and proportions of the missing-book-value firms either.

Closely related to the FF CAPM is the Carhart (1997) variant, which contains a momentum portfolio. From Table 9 we see that also in our global data base there is a momentum effect: portfolios formed on low past performance tend to underperform portfolios consisting of high past performers in terms of raw return. But the smallest size portfolio turns out to be rather a loser portfolio and the biggest size portfolio a winner—the reverse of what we should see if momentum is behind the smallest-firm anomaly. From Table 6 Panel C, in fact, we see no improvement: the loadings on the momentum factor are insignificant for all size portfolios, and the alphas and R^2s are essentially unaffected. Thus, momentum risk seems to play no meaningful role in the explanation of the size premium in the presence of the FF factors.

4.3 Liquidity

Part 1 of Table 10 shows descriptive statistics of portfolios sorted on illiquidity.[15] We see a generally positive relation between the illiquidity of the portfolios and their 6-month holding period return, with a raw liquidity premium of 0.30% per month. The standard beta drastically decreases with illiquidity, in line with the thin-trading logic (see supra). Higher returns combined with prima-facie lower betas imply that illiquid stocks have higher alphas, pushing the beta-adjusted liquidity premium from 0.30 to 0.50% per month. Unsurprisingly, liquidity

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[14]One exception is the UK which has by far the lowest proportion of missing-book-value firms (6.61%). This is probably due to the UK origin of Thomson Reuters Datastream.

[15]As a measure for illiquidity, we use the zero-return proportion proposed by Lesmond *et al.* (1999) *i.e.* the ratio of the number of zero-return days to the number of trading days.

is also related to size. An alternative way of illustrating the link is to look at illiquidity per size portfolios rather than the other way around (Part 2 of Table 10). We see again the negative relation between the size of the portfolios and their illiquidity measure. These results make illiquidity a candidate explanation of the small firm effect. The link is far from perfect, though, and some micro firms are traded quite often; for example, in the most illiquid portfolio, 20% of the firms are from size decile 1, while in the most actively traded portfolio there still are about 2% tiny firms.

In Panel A of Table 11, we test more formally for a link by applying Liu's (2006) liquidity-augmented CAPM to the portfolios sorted on size. The model fails to account for the smallest firm effect, though. We do see significant loadings on the liquidity factor, with logical signs and magnitudes, like falling sensitivities to the LIQ_t factor as size rises. Anomalously, though, the smallest size portfolio does not fit in, and its risk loading is insignificant. The alphas of the first and second size portfolio remain significantly positive and the corresponding R^2s low. Apparently the association between size and illiquidity is too weak, as we already saw from Table 10.

A liquidity-augmented CAPM that includes the FF factors is even more illuminating. From Panel B of Table 11 we see that the risk loadings on the liquidity factor are now all insignificant and even switch signs to become illogically negative for the smaller portfolios. Collinearity between LIQ_t and SMB_t is probably the cause ($\rho = 0.34$). The FF factors, in contrast, remain significant with the correct sign and magnitudes. We therefore conclude that, while there is an association between size and liquidity, the liquidity factor does help to explain the smallest firm effect, and is actually subsumed by the FF factors.

4.4 Business cycles and the bond-yield risk spread

From Figure 3 we saw that, during economic downturns, prices of the smallest stocks drop by more. In addition, from Table 3, we saw that the smallest firms suffer a relatively higher rate of delisting. These observations may suggest that the smallest stocks bear more downside risk which motivates a further investigation of the smallest firm effect with respect to the risk of the business cycle.

In Panel A of Table 12 we test the ability of Chan *et al.* (1985)'s measure of changing risk premium (the bond-yield risk spread, $PREM_t$), to account for the small firm effect. We do see significant positive loadings on $PREM_t$ for all portfolios except the top league, and these loadings fall with size. This effect more or less survives the addition of the FF factors (Panel B of Table 12), even though the magnitude and significance drop sharply and the decreasing pattern with size disappears. In short, $PREM_t$ is not subsumed by the market or the FF factors. But it does not solve the smallest-firm anomaly: we still see the same significantly positive alpha for the smallest portfolio.

4.5 The January effect

Table 13 displays the average January and average non-January returns for each of the ten size portfolios. The last column shows that the New Year seasonal becomes larger the smaller the firm, which makes the January effect a candidate explanation of the small firm effect.

Panel A of Table 14 shows the parameter estimates of the CAPM extended with a January dummy. Unsurprisingly, we see positive coefficients, and they do become larger for the smaller portfolios. In fact, the January-adjusted CAPM is able to price all size portfolios, with one exception, the smallest firms. Adding the FF factors has mixed consequences, though. The January dummy now fails to affect all returns—but again with one exception, the smallest firms. In that sense, the January effect is a valuable piece of the smallest firm puzzle even in the presence of the FF factors, but it does not tell the entire tale.

4.6 Exchange risk

In Table 15 and Figure 7 we see that the distribution of the currency denomination of the smallest firm sample differs from the pooled sample.[16] For example the share of stocks denominated in Japanese Yen in the bottom decile is only 5.6%, against 16.9% for the entire sample, while for stocks denominated in Korean Won, we see the opposite (12.5% against 4.7%). Generally speaking we see that the smallest-firm sample is more denominated in U.S.Dollar than the general sample: the U.S.Dollar sample provides 45% of size decile 1, against 37% of the entire population. Of course, currency denomination does not mean that there is unit exposure to the corresponding exchange rate and none to others. Still, the differential distribution makes an investigation worthwhile. In addition, there are strong priors that exchange risks cannot be ignored in general.

The Sercu (1980) generalization of Solnik's (1974) K-country model features the world-market-portfolio return and the excess returns from investing in each of the $K-1$ non-numériare currencies. Including all foreign currencies as factors is not recommendable as the power of the alpha tests would drop dramatically; but otherwise there are no clear guidelines or standard practices. Jorion (1990) proposes to use a single trade-weighted basket of currencies but this assumes that all stocks have a vector of currency exposures that is proportional to the trade weights, a restriction which Rees and Unni (2005) reject empirically. We adopt a compromise.

[16] By currency of denomination we mean the currency of the country where the stocks has its primary listing.

Seven 'big' currencies are included in all regressions, taking at least one currency per continent and looking, per continent, at economic weight and number of stocks in our database. This list contains the Canadian Dollar, the British Pound, the Deutsche Mark (before January 1, 1999) or the Euro (after January 1, 1999), the Japanese Yen, the Korean Won, the Australian Dollar and the South African Rand. All stocks are allowed to be exposed to each of these 'big' currencies without any prior restrictions. In addition to these seven regressors with unrestricted relative importance, every decile gets its own tailor-made basket of smaller currencies reflecting the currency-denomination mix of the stocks in that decile.[17]

From Panel A of Table 16 we see that adjusting the CAPM for exchange risk does not solve the mispricing of the smaller stocks, but we do see significant loadings on the exchange factors. For instance, in the smallest decile we see significant positive loadings on the Korean Won and the decile's small-currency-basket exchange factor, and significant negative loadings on the Mark/Euro and the Japanese Yen. (If this were a single firm, it would be a firm from Korea or from the small second-tier currencies, either B2B-style selling to German or Japanese exporters at prices fixed in Korean Won or U.S.Dollar, or importing from those countries.[18]) But the alphas for the smaller-sized portfolios remain disconcertingly positive, and especially so for the smallest decile (2.40%, with t-statistic of 10.81); and the R^2 for the smallest stocks remain quite low (51%, against 97% for the largest-decile portfolio).

The Sercu (1980) model has no state variables, so an obvious extension is to add the FF factors. From Panel B of Table 16 we see the parameter estimates of the FF model extended with the exchange risk factors. Again, the exchange factors in the above test may just have been proxying for the FF factors. If we focus on the smallest-firm portfolio, we see that this is not the case. The decile's own compound exchange factor and the Japanese Yen remain significant, although their magnitude nearly halves from 0.54 to 0.29 (for the compound currency factor) and from -0.18 to -0.08 (for the Japanese Yen factor). The Korean Won and the Mark/Euro do become insignificant, only to be replaced by the British Pound (-0.19) and the South African Rand (0.08). The loadings on the FF factors are as usual and their inclusion into the static international model do push the beta and R^2 of the smaller deciles closer to unity and the alphas closer to zero, but not far enough to resolve the anomalies

[17]Formally, the assumption is that stocks denominated in the 31 'smaller' currencies each have a common exposure to their own exchange rate (Adler and Simon, 1986). The implication is that the decile's basket of currency deposits should give to each 'small' currency the same weight as the the stocks denominated in that currency have in that particular size portfolio. For example, if size decile 1 has twice as many firms from denominated in Thai Baht as in Taiwan Dollar, then in decile 1's small-currency basket the Baht has twice the weight of the Taiwan Dollar.

[18]In Table 15 we saw, indeed, that the smallest firm sample has relatively many stocks denominated in Korean Won.

We conclude that exchange risk is important in the international small firm effect as it significantly adds to the explanation of the size portfolio returns even in the presence of the FF factors.

4.7 Bringing it all together

In the preceding subsections we tested several potential explanations for the small-firm effect. We found that augmenting the one-factor CAPM with, in turn, infrequent trading, financial distress risk (SMB_t and HML_t), illiquidity, the bond-yield risk spread, the January effect and exchange risk results in significant loadings, but without eliminating the anomalous alphas. To some extent we also tested factors jointly, notably by starting from the FF model rather than the one-factor CAPM. The main result was that SMB_t and HML_t seem to subsume liquidity risk; the other explanations remained valuable, although less so than in the one-factor CAPM model.

A logical next step is to combine these explanations into one model that adjusts for all these risks jointly. This is important because, with overlapping risks, separately significant loadings can become insignificant if estimated jointly. Moreover risk factors may not be able to explain the smallest firm effect separately, but they may still jointly yield a well-specified asset-pricing model that produces intercepts indistinguishable from zero.

Based on the evidence in the previous subsections we construct, in Table 17, the Full Model which adjusts jointly for market risk, infrequent trading, financial distress risk, business cycle risk, the January effect and the relevant exchange risks.[19] We see that jointly adjusting for the relevant risks still does not explain the smallest firm effect. The smallest decile portfolio continues to generate an large average abnormal return (1.30% per month), while for the next few deciles we see significant negative alphas. The lagged beta, which was not included in any of the above multi-factor models, is still positive but loses its significance. (Interestingly, the lagged market factor is correlated with both SMB_t and the bond-yield risk spread. with $\rho = 0.25$ and 0.4, respectively). It seems that the effect of infrequent trading is jointly accommodated by size risk and business cycle risk. The other loadings are comparable to those estimated in the earlier separate tests.

4.8 Dividend yield effects

We start by sorting stocks by dividend yield and then computing mean returns per yield decile. From the left-hand part of Table 18 we see that also in our data base average returns

[19] Dividend, to be discussed in the next subsection, is not included because it is a characteristic not a factor.

rise with yield, provided the latter is positive, while expected returns are also peaking for zero dividends—the familiar lopsided V. From the right-hand side of Table 18, in contrast, the bigger the firm is, the lower its yields (provided yield is positive) and also the lower the proportion of zero-dividend yield stocks. Most notably, the smallest decile portfolio exhibits both the highest positive-dividend-yield average (4.48%) and the highest proportion of zero-dividend yield stocks (17.59%). So the questions are (i) whether yield, as a characteristic, explains average returns and (ii) if it does, whether we can relate yield to a risk measure or to a risk factor.

4.8.1 Can dividend yield explain average returns, as a characteristic?

We test the marginal ability of dividend yield to explain the cross-section of portfolio returns classified by size. Panel A of Table 19 shows the statistics of the parameter estimates of the Fama-Macbeth (1973) (FM) regressions that relate the risk-adjusted returns from the Full model on two dividend-yield portfolio characteristics: the equally-weighted positive portfolio dividend yield and the proportion of zero-dividend yield stocks. We see that the portfolio dividend yield shows up as a significant characteristic in explaining the cross-section of the risk-adjusted size portfolio returns (mean slope 0.45; t-statistic 4.98). The next question is whether we can relate this to a measure that better captures an exposure or to a new source of risk.

4.8.2 Can dividend yield be related to time-varying risk loadings?

From the above, dividend may be picking up an aspect of general financial distress. Cross-sectionally, dividend yield tells the investors something about the firm's health, in this view. In addition, however, changes in the yield may also be longitudinally correlated with changes in the firm's exposure(s), and perhaps especially so for small firms. Circumstantial evidence is provided by the twin facts that small firms have both a more uncertain future (more chance to either migrate to a better class or to disappear—Table 3) a more volatile yield, and a more variable number of zero-yield cases (Table 18, right hand side).

To explore whether changes in yield are longitudinally correlated with exposure, we first regress the Full-Model's unexplained returns on dividend yield variables. From Table 20 we see that, over time, positive dividend yield is related positively to risk-adjusted returns for all sizes. The proportion of zero-dividend yield stocks seems to play different roles depending on size, though: a dividend stop comes with lower risk-adjusted returns for the smaller stocks and higher returns for bigger stocks. Lastly, R^2s also tell us that time variation of the dividend yield characteristics are more important for the smallest portfolio.

The next question is to what extent this phenomenon picks up variations in exposure to a risk that is already in the Full Model.[20] To identify possibly time-varying risk loadings (related to dividend yield) we re-run the time-series regressions of the risk-adjusted returns on the dividend yield characteristics but we now add also interactions of the risk factors of the Full Model with the dividend yield characteristics (22 cross terms per size portfolio). For simplicity we only report the significant parameter estimates in Table 21; the others are available upon request. In Table 21 we observe, for all size categories, positive coefficients for the market risk crossterm with the portfolio's positive dividend yield; and negative ones with the portfolio's proportion of zero-dividend yield stocks. That is, the market beta seems to drop over time when either non-zero dividend yields drop or more firms in the portfolio suspend payouts, even after controlling for (most) size effects. Apart from this interaction effect between dividend yield and market beta, all other significant interactions are confined exclusively to the smallest size portfolio (the portfolio with the most mispricing by the static Full Model). An example is the exposure to SMB_t which is, only for the smallest stocks, positively related to dividend yield and negatively to the proportion of zero-dividend yield stocks. Variations in these exposures even add 16% to R^2. In short, time-varying risk loadings (related to dividend yield) appear to be more of an issue for the smallest stocks.

4.8.3 Why do dividends play these interesting roles in modeling exposures, especially for the smallest stocks?

Perhaps the explanation is the commitment signal behind a high (vs. a low) and a positive (vs. a zero) dividend yield. Familiarly, managers dislike dividend cuts, so a payout is signaling some commitment for the future. Conversely, then, investors may have few illusions about low-payout or zero-dividend firms, so they adjust their valuations less when the market as a whole drops or when smaller stocks do likewise poorly.

Another possible avenue starts from the noncontroversial idea that zero dividends signal either extreme youth or financial distress; that is, they are a danger signal rather than a sign of good corporate health. But also high yields might be a danger signal, notably if the firm recently paid an ordinary dividend and then saw its price crash—a very recent fallen angel, in short. The third column of Table 18 indeed shows that the highest-dividend shares had the lowest returns in the preceding six months. So, the possible avenue is that a high yield stands for a recent price drop, which plays a role distinct from that of size per se.

[20] The other avenues that could longitudinally explain returns are (i) a new risk, or (ii) changes in some price of risk. But the latter would be explained by market-wide yield variables, not individual-stock dividends; and the factor portfolios would already have picked up the market-wide impact of general dividend yields anyway.

4.8.4 Can dividend yield be related to a missing risk factor?

The dividend-related variation in exposure is not the entire story: in the regressions summarized in Table 21, both of the dividend-yield characteristics remain significant even in the presence of the crossterms. That is, dividend yield characteristics are probably not just proxies for time-varying risk loadings, and may instead be related to a missing risk factor.

We further explore this by composing, in Table 22, a conditional Full Model that consists out of the significant risks from the static Full Model (Table 17) and the significant crossterms in Table 21 but not the dividend variables as characteristics.[21] From Table 22 we see that there is still mispricing of the smaller stocks: the smallest stocks provide excessive-looking returns (i.e. they look underpriced) while the next decile seems overpriced. This suggests that the smallest stocks may be positively correlated with a potential missing risk factor and the next few deciles of small stocks negatively. We now regress these new estimates of unexplained returns on the usual dividend characteristics, and find that they still matter (Panel B of Table 19): the portfolio dividend yield shows up as a significant characteristic in explaining the cross-section of the risk-adjusted size portfolio returns (mean coefficient 0.41; t-statistic 4.46). This again suggests a potential missing factor that may be related to dividend yield.

5 The missing risk factor

Fully identifying the missing risk factor is beyond the scope of this paper but we can provide some clues, perhaps useful for further research. From the preceding section, the missing factor seems to be related to dividend yield; and the smallest stocks are positively exposed to it while the next few deciles are affected negatively by the missing factor. In this section we compose an ad hoc asset pricing model that captures these phenomena. In a sense, the 'success' of this factor may to some extent seem a tautology, following from its construction. It is true that the objective is not to economically explain the anomalies. Instead, we just construct a single time series that captures their means; we then test whether it affects the means via covariances (which is less of a tautology); and we lastly explore the properties of this time series, hoping to glean some properties of the missing risk factor. This ad hoc pricing model features the usual market factor, a size factor that resembles the familiar FF size factor, and a micro-size portfolio where decile 1 is held long and deciles 2-5 short.

Table 23 shows the results. All size deciles are now 'explained' by the ad hoc model in

[21] More specifically we allow time-varying risk loadings linearly related to positive dividend yield and the proportion of zero-dividend yield stocks for the market beta, the GBP exchange risk factor, the decile's compound exchange risk factors and the FF size factor.

the sense that all alphas are insignificant. All market betas are close to unity but the market factor still imparts an empirically adequate mean level of return to all portfolios. The size factor adjusts for the familiar size risk, and the loadings on size are negatively related to size. The micro-size factor captures the quirks in the infra-median stocks: we see a positive loading for the smallest size decile and negative loadings for the decile 2-to-5 stocks.

While the result may look unsurprising, they are still relevant and interesting for two reasons. First, there is a crucial distinction between 'solving' the pricing errors by a characteristic and a factor (Daniel *et al.*, 1997). In the case of a characteristic, returns are explained by, for example, size or leverage or dividend yield, which are attributes of the company. This is very different from a factor: a factor is always time-varying, it affects many or even all stocks, and it is the company's sensitivity to the factor that explains expected returns. Hence, if the explanation is a priced factor, it can be picked up by a portfolio of assets, provided that the return-generating process is sufficiently close to linearity and the residual returns nearly independent. Thus, if we can identify portfolios that resolve the mispricing via their covariances, we narrow down the list of explanations to factors.

This would already rule out data errors and information asymmetries. Data errors, being random, do not co-vary with a market-wide variable. (One exception must be made for data errors caused by stale prices or thin trading, but we controlled for this possible explanation separately.) Information asymmetry is less likely to be a factor either: there is relatively less variation over time, and even less variation that goes together with market-wide information problems. True, asymmetries are often measured by bid-ask spreads, and these do co-vary across stocks. But spreads are also driven by liquidity, where there is a very clear market-wide factor; so co-variation in spreads is more likely to reflect a liquidity factor than an information factor.

A second reason why the success of the micro-minus-small factor matters is that exploring the properties of this micro-size factor may give some positive clues of how the missing factor may look like. In Table 24 we display Spearman rank correlations for the two size factors with selected portfolios, conditional on the other risk factors in the ad hoc model and the original FF factors. Panel A focuses on the regular size factor. We see that it is significantly correlated with a dividend yield factor constructed as a zero-investment portfolio long in high-dividend yield stocks and short in low-dividend yield stocks. We also see conditional correlations with the British pound exchange factor and the momentum factor. In Panel B we calculated the conditional correlations of the micro-size factor and we again see a substantial correlation with the dividend yield factor. The micro-size factor is also conditionally correlated with the German mark and the Japanese yen exchange factors and the January dummy. Taking the significant conditional correlations of the ad hoc size factors together we conclude that the risk factor that is missing in the FF model in order to explain the international smallest firm effect is probably linked with dividend yield differentials, the German, Japanese and British exchange rates, the January anomaly and the momentum anomaly—quite a heterogeneous list.

6 Conclusion

We construct an international dataset where the smallest stocks are neither excluded a priori nor downplayed indirectly, by value-weighting. Our filtering is confined to companies with market values below ten million dollars or stock prices lower than one dollar. We also screen the dataset for errors, in line with Ince and Porter (2006). Based on this international dataset we identify a post-1980s size effect.

We documented the size effect based on descriptive statistics and formal tests and conclude that neither the risk factors considered in the current literature nor time-varying loadings (linearly depending on dividend yield) can fully explain the size effect (in the sense of producing alphas close to zero). The quest for the missing factor is outside the scope of this paper and subject of further research but we do discover some clues. The unexplained returns seem to be linked with a dividend-yield factor portfolio. We pragmatically constructed two ad hoc size factors which get the alphas to zero. One size factor resembles the FF size factor, the other focuses on the smallest stocks. These ad hoc size factors (and therefore probably also the missing risk factor) seem to be conditionally correlated with a dividend yield factor.

The smallest firm effect could be exploited by setting up funds, perhaps closed-end (given the low liquidity of the smallest firms), that invest in these smallest stocks internationally. Figure 6 lists the relevant stock exchanges where most of the smallest stocks can be found.

Appendix: more descriptives on individual stocks

Descriptives per country

Table 1 and 2 provide descriptive statistics on the pooled sample and its subsamples, respectively, sorted by country and sector. The tables provide the start date, the average number of firms, the average market capitalization, the unconditional return and standard deviation, the average firm size and the average number of smallest firms (i.e. firms for which the monthly market capitalization is in the first decile of the pooled sample). The bottom line provides the descriptive statistics for the pooled sample. Figure 1 and 2 graphically illustrate column 4 and the last-but-one column of Tables 1 and 2, i.e. the average geographical and sectoral distribution, in terms of number of stocks, in the pooled sample and the sample of the smallest stocks. The Tables and Figures 1 and 2 should provide a better understanding of the pooled sample and its subsamples. This is useful as the composition of the dataset is crucial for our findings.

From Table 1 we see that many EMs start in the late 1980s and begin 1990s in TRD. This does not lead to a truncated sample for EMs as the end date, mid-2009, still leaves roughly 20 years of data for the EMs. The Big-3 countries, both in terms of number of firms and country market capitalization are the U.S., Japan and the UK. Korea is the largest EM and comes just after the Big 3. Notice the numerous small countries with a contribution below 1%. Taken together, though, these smaller countries still outweigh the UK sample both in terms of number of firms and market capitalization (10.73% to 9.23% and 11.76% to 9.90%). So, smaller countries are all together quite big and should, therefore, deserve the proper attention in an international dataset.

All countries show positive unconditional returns with Peru, China, Brazil, Mexico and India even producing an above-2% monthly return. Not surprisingly, these EMs also have among the highest standard deviations (except for Mexico which offers a below-10% standard deviation). The above-10% standard deviation countries are all EMs. The 'safest' countries are all developed countries like Switzerland, Belgium, UK, U.S., Denmark, Luxembourg and the Netherlands. Note that these countries are not necessarily big countries, with high local diversification possibilities (except for UK and U.S.). The best performing countries in terms of return-risk ratio (i.e. the average return relative to the standard deviation) are a mixture of developed and EMs, namely Chili, Peru, UK, Ireland, Australia, Denmark, Mexico and U.S.. Not surprisingly, the return-risk ratio is highest for the pooled sample.

The average firm size of the pooled sample is $1,259 million which is smaller than half the average size of a Spanish or Hong Kong firm; but larger than twice the average Korean, Greek, Danish, Norwegian, Austrian, New Zealand and Chinese firm. Note that five of these smaller-firm countries are DMs. This suggests that EMs do not have the monopoly on smaller firms. From the Big 3, in fact, the U.S.and the UK have more weight in the sample of the smallest firms than in the pooled sample (45.32% against 38.27%, for the U.S.; 11.08% against 9.23%, for the UK), whereas Japan has less (5.42% against 16.66%). For some countries the proportion of smallest firms in their country sample is far from 10%. For example 24% of the Korean stocks are in the smallest size decile which makes Korea jump from the 4th to the 2nd largest country in the smallest firm sample compared to the pooled sample. At the other end, not even 1% of the Philippines and Singapore firms are in the smallest category.[22] Note

[22]Remember that the dataset is screened and filtered for tiny, illiquid and penny stocks. Thus the relative little amount of smallest stocks in some countries may be due to the screening and filtering process in those countries. We do not have information on the identity of the filtered observations, so we cannot make the distinction between countries with genuinely relatively little smallest stocks and countries where the screening

that the relative amount of smallest stocks in the country sample is not a point of difference between EMs and DMs.

Descriptives per sector

From Table 2 we see that every sector starts from day-one in the dataset. The largest sectors in terms of number of firms are Construction & Materials, Electronic & Electrical Equipment, Industrial Engineering and Banks. The latter sector represents more than 7% of the total sample. The smallest sectors are Aerospace & Defense, Forestry & Paper, Fixed Line and Mobile Telecommunications, Life Insurance, Tobacco and Alternative Energy. The latter two represent each less than 0.2% of the total sample. In terms of market capitalisation the picture is somewhat different. Fixed Line Communications is now a large sector, representing more than 5 % of total market capitalization. The other large sectors are now also different, except for Banks, namely Pharmaceuticals & Biotechnology, Oil & Gas Producers and Banks. The latter represent more than 10% of total market capitalization. Small sectors in terms of market capitalization are Alternative Energy, Forestry & Paper, Unclassified (i.e. firms with unknown sector classification), Oil Equipment, Services & Distribution and Tobacco. Overall, Banks is the largest sector in the dataset.[23]

All sectors have an average monthly return between 1% and 2%. The 'safest' sector, in terms of standard deviation, is Gas, Water and Multiutilities (3.24%) and the riskiest is the small sector Alternative Energy (11.82%). Contrary to country beds, several sector beds offered a higher return-risk performance than the overall market (Gas, Water & Multiutilities, Electricity, Tobacco, Beverages, Food Producers, Food & Drug Retailers, Banks, Nonlife Insurance).

Not surprisingly, the average firm size differs much more across sectors than across countries. Sectors with an average firm size of more than twice the overall average firm size are Nonlife Insurance, Electricity, Oil & Gas Producers, Life Insurance, Mobile Telecommunications, Tobacco and Fixed Line Telecommunications. The average firm of the latter sector is even 7 times larger than the overall average firm. The sectors with an average firm size of smaller than half the overall firm size are: Construction & Materials, Support Services, Industrial Engineering, Real Estate Investment & Services, Electronic & Electrical Equipment, Unclassified and Alternative Energy. The average firm size of the latter is only 1/5th of the

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process has filtered relatively many smallest stocks. This also suggests that the composition of size portfolios with breakpoints based on the pooled sample may be different then when country-specific breakpoints are used.

[23]Note that the size of a sector may also depend on the level of detail of the sector definition. Banks are defined as providing a broad range of financial services, including retail banking, loans and money transmissions.

overall average firm.

From Figure 2 or the last-but-one column of Table 2 we see that the sample of smallest firms is not dominated by any sector. The biggest sector in the smallest firm sample is Electric & Electronical Equipment with still only 8% weight, followed by Industrial Engineering, Software & Computer Services, Banks and Support Services, all with an above-5% stake in the sample of smallest stocks. The cross-sectoral variation of the proportion of smallest firms is much smaller than for countries. On the one hand the Electricity sector consists of only roughly 2% of smallest firms; and on the other hand the sector Software & Computer Services has about 16% smallest firms.

Descriptives per exchange

As we have screened the dataset for dual listings and the primary quote of a firm is generally on its major national stock exchange, the stock exchange distribution of the pooled and the smallest firm sample is quite similar to their geographical distribution. However, some countries have multiple stock exchanges and their relative importance was not yet presented. Table 4 provides the stock exchange distribution of the pooled sample,the smallest firm portfolio and their difference. Figure 6 is the graphical representation of Table 4, only for the larger stock exchanges. Not surprisingly, for the pooled sample, the largest stock exchanges are NYSE (14.82%), Tokyo (14.49%), Nasdaq (13.36%) and London (7.85%). For the sample of smallest stocks the picture is somewhat different.

The NYSE and especially Tokyo are less present. The NYSE typically lists larger firms, compared to the Amex or Nasdaq, but remains important even also for the smallest firm sample (11.14% for small stocks against 14.49% for all stocks). Tokyo is far more underweight of smallest stocks, where its share is as low as 1.45%. The Nasdaq, instead of NYSE/TSE, becomes the most important stock exchange in the smallest firm sample (13.82%), but also its two OTC compartments, the OTC Bulletin Board (4.83%) and the Other OTC (11.61%), are important in the smallest firm sample. Note that the stocks quoted on this OTC Bulletin Board and on other OTC markets of Nasdaq, and even Nasdaq stocks itself, are often not covered by other studies. Other important stock exchanges in the smallest firm sample are London (11.07%), Korea (6.99%) and Kosdaq (5.26%).

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Table 1
Country statistics

The *start date* is the month of the first return observation. *Avg* is the time-series average, calculated from the start date, of the monthly number of ongoing firms (column 3), the monthly country market capitalization (column 5), the monthly equally-weighted country return (column 7), the monthly average firm market capitalization (column 10) and the monthly number of smallest firms (column 12). *Smallest firms* have a market capitalization in the first size decile of the pooled sample. Size breakpoints are updated monthly. *Distribution* is the time-series average, calculated over the full sample period, of the monthly ratios (in %): number of ongoing firms relative to the total number of ongoing firms (column 4), monthly country market capitalization relative to the total market capitalization (column 6) and number of smallest stocks relative to the total number of smallest stocks (column 13). *Std* is the standard deviation of the monthly equally-weighted country return. *Relative* is avg divided by Total avg. *Proportion* is the time-series average, calculated from the start date, of the monthly ratio (in %): number of smallest stocks relative to the number of ongoing firms in the country. *Due to several currency transitions the pre-1992 Argentina Peso/USD exchange rate is not reliable for translating Peso-denominated data. Argentina enters the sample in Jan.1992 although local currency data is available from Febr.1980. **Due to several currency transitions the pre-Aug.1994 Brazilian Real/USD exchange rate is not reliable for translating Real-dominated data. Brazil enters the sample in Aug.1994 although local currency data is available from Febr.1990. ***The Total's are calculated from the pooled sample directly and are, therefore, generally not equal to the sum or average of the subsamples. For example, the average number of *total* ongoing firms is lower than the sum of the country subsamples. The reason is that *Total* is calculated from the pooled sample starting in Jan.'80, whereas, for example, the average number of Chinese ongoing firms is calculated from its start date i.e. Febr.1991.

		# of Firms		Market Capitalization		Monthly Return			Firm Size		# of Smallest Firms		
Country	Start Date	Avg	Distribution	Avg ($x10^6$)	Distribution	Avg	Std	Avg/Std	Avg ($x10^6$)	Relative	Avg	Distribution	Proportion
Developed markets													
Australia	jan/80	134	1.13%	235,658	1.22%	1.56%	6.88%	0.23	1,362	1.08	5	0.44%	3.59%
Austria	jan/80	49	0.47%	35,348	0.16%	1.14%	6.08%	0.19	590	0.47	5	0.63%	14.61%
Belgium	jan/80	83	0.87%	99,912	0.54%	1.21%	5.47%	0.22	1,018	0.81	9	1.08%	11.30%
Canada	jan/80	473	4.34%	422,068	2.67%	1.27%	6.37%	0.20	733	0.58	61	5.47%	12.53%
Denmark	jan/80	80	0.77%	47,909	0.26%	1.35%	5.84%	0.23	494	0.39	10	0.93%	11.39%
Finland	feb/87	69	0.40%	104,571	0.31%	1.37%	6.93%	0.20	1,199	0.95	5	0.31%	8.48%
France	jan/80	361	3.45%	680,837	3.38%	1.42%	6.35%	0.22	1,515	1.20	36	3.20%	8.85%
Germany	jan/80	354	3.48%	593,858	3.71%	0.97%	6.04%	0.16	1,446	1.15	39	3.45%	10.00%
Greece	feb/88	146	0.79%	68,339	0.19%	1.74%	11.54%	0.15	378	0.30	23	1.26%	16.38%
Hong Kong	jan/80	35	0.35%	169,059	0.81%	1.79%	8.86%	0.20	3,603	2.86	0	0.03%	1.02%
Ireland	jan/80	24	0.24%	33,638	0.15%	1.63%	6.72%	0.24	1,207	0.96	1	0.18%	7.96%
Italy	jan/80	156	1.52%	292,724	1.51%	1.09%	6.79%	0.16	1,477	1.17	4	0.50%	3.34%
Japan	jan/80	1,786	16.66%	2,491,429	20.46%	1.08%	7.09%	0.15	1,351	1.07	79	5.42%	2.86%
Luxembourg	apr/91	12	0.06%	21,819	0.05%	1.19%	5.92%	0.20	1,525	1.21	1	0.03%	6.79%
Netherlands	jan/80	109	1.17%	208,133	1.34%	1.20%	5.94%	0.20	1,791	1.42	12	1.58%	11.82%
New Zealand	feb/86	25	0.16%	16,042	0.07%	1.49%	7.14%	0.21	600	0.48	2	0.12%	7.11%
Norway	jan/80	82	0.75%	62,897	0.28%	1.49%	7.40%	0.20	546	0.43	6	0.61%	8.10%
Portugal	feb/88	43	0.26%	44,251	0.13%	0.91%	6.60%	0.14	1,136	0.90	3	0.23%	7.51%
Singapore	jan/80	48	0.50%	68,511	0.42%	1.42%	7.55%	0.19	1,359	1.08	0	0.06%	0.97%
Spain	feb/86	109	0.73%	299,615	1.05%	1.54%	7.26%	0.21	2,527	2.01	2	0.17%	2.25%
Sweden	jan/80	113	1.03%	100,703	0.77%	1.56%	7.33%	0.21	1,801	1.43	14	1.17%	10.33%
Switzerland	jan/80	134	1.42%	317,496	1.70%	1.01%	5.24%	0.19	2,141	1.70	8	0.97%	6.35%
U.K.	jan/80	813	9.23%	1,456,542	9.90%	1.41%	5.74%	0.25	1,746	1.39	80	11.08%	10.18%
U.S.	jan/80	3,747	38.27%	6,714,971	43.95%	1.31%	5.82%	0.23	1,516	1.20	443	45.32%	11.95%
Emerging Markets													
Argentina*	jan/92	15	0.07%	6,808	0.02%	1.28%	12.23%	0.10	767	0.61	1	0.06%	6.24%
Brazil**	aug/94	97	0.35%	182,216	0.31%	2.43%	10.79%	0.22	1,545	1.23	7	0.28%	7.53%
Chili	jul/89	30	0.16%	38,422	0.11%	1.91%	7.02%	0.27	1,125	0.89	0	0.02%	1.09%
China	feb/91	317	1.40%	290,412	0.57%	2.64%	13.21%	0.20	616	0.49	0	0.02%	1.01%
Colombia	feb/92	12	0.05%	14,535	0.03%	1.78%	8.58%	0.21	960	0.76	0	0.01%	1.24%
India	jan/90	306	1.54%	239,180	0.58%	2.01%	11.19%	0.18	631	0.50	31	1.62%	10.00%
Indonesia	apr/90	26	0.15%	18,261	0.07%	1.14%	12.18%	0.09	1,823	1.45	2	0.11%	4.80%
Korea	jan/82	616	4.63%	208,194	0.87%	1.66%	11.13%	0.15	252	0.20	167	12.26%	24.00%
Malaysia	jan/80	84	0.75%	59,617	0.35%	1.49%	8.81%	0.17	818	0.65	3	0.25%	4.61%
Mexico	feb/88	32	0.19%	71,535	0.21%	2.02%	8.97%	0.23	2,028	1.61	0	0.02%	1.05%

Peru	feb/91	13	0.06%	17,049	0.08%	2.90%	10.92%	0.27	2,022	1.61	1	0.06%	7.52%
Philippines	okt/87	9	0.05%	14,223	0.05%	1.70%	9.16%	0.19	1,576	1.25	0	0.00%	0.50%
South Africa	jan/80	99	0.99%	109,833	0.83%	1.54%	8.26%	0.19	999	0.79	2	0.27%	2.53%
Taiwan	okt/87	167	0.98%	175,292	0.68%	1.40%	11.92%	0.12	1,082	0.86	3	0.14%	2.02%
Thailand	jan/87	81	0.58%	43,954	0.19%	1.65%	8.48%	0.19	814	0.65	9	0.65%	10.67%
Total***	jan/80	10,366	100.00%	15,532,281	100.00%	1.34%	4.78%	0.28	1,259	1.00	1,037	100.00%	10.00%

Table 2
Sector statistics

Thomson Reuters Datastream uses the Industry Classification Benchmark (ICB) classification model for equities (http://www.icbenchmark.com/docs/Structure_Defs_English.pdf). This industry structure contains 4 levels namely 10 industries, 19 super sectors, 41 sectors and 114 subsector. We used the classification of 41 sectors as this offers a level of detail that is similar to the country classification i.e. 39 countries. Note that the screening procedure filtered out 3 sectors, namely Real Estate Investment Trusts, Equity Investment Instruments and Nonequity Investment Instruments. *Unclassified* firms are firms with unknown sector classification. The *start date* is the month of the first return observation. *Avg* is the time-series average of the monthly number of ongoing firms (column 3), the monthly country market capitalization (column 5), the monthly equally-weighted country return (column 7), the monthly average firm market capitalization (column 10) and the monthly number of smallest firms (column 12). *Smallest firms* have a market capitalization in the first size decile of the pooled sample. Size breakpoints are updated monthly. *Distribution* is the time-series average of the monthly ratios (in %): number of ongoing firms relative to the total number of ongoing firms (column 4), monthly country market capitalization relative to the total market capitalization (column 6) and number of smallest stocks relative to the total number of smallest stocks (column 13). *Std* is the standard deviation of the monthly equally-weighted country return. *Relative* is Avg divided by Total Avg. *Proportion* is the time-series average of the monthly ratio (in %): number of smallest stocks relative to the number of ongoing firms in the sector. *The Total's are calculated from the pooled sample directly.

Industry		# of Firms		Market Capitalization		Monthly Return			Firm Size		# of Smallest Firms		
Sector	Start Date	Avg	Distribution	Avg (x10^6)	Distribution	Avg	Std	Avg/Std	Avg (x10^6)	Relative	Avg	Distribution	Proportion
Oil & Gas													
Oil & Gas Producers	jan/80	251	2.60%	958,059	6.92%	1.33%	6.67%	0.20	3,226	2.56	24	2.52%	9.88%
Oil Equipment, Services & Distribution	jan/80	110	1.02%	138,281	0.71%	1.33%	7.44%	0.18	894	0.71	6	0.62%	6.47%
Alternative Energy	jan/80	18	0.13%	13,261	0.04%	1.77%	11.82%	0.15	275	0.22	2	0.14%	13.67%
Basic Materials													
Chemicals	jan/80	396	3.93%	424,317	3.42%	1.38%	4.92%	0.28	971	0.77	33	3.17%	8.11%
Forestry & Paper	jan/80	91	0.90%	69,572	0.57%	1.15%	5.22%	0.22	697	0.55	8	0.74%	8.20%
Industrial Metals & Mining	jan/80	230	2.24%	250,233	1.67%	1.48%	6.14%	0.24	888	0.71	18	1.76%	8.02%
Mining	jan/80	197	1.94%	228,043	1.57%	1.51%	7.87%	0.19	941	0.75	23	2.13%	11.24%
Industrials													
Construction & Materials	jan/80	532	5.18%	355,365	2.65%	1.41%	5.18%	0.27	588	0.47	45	4.32%	8.61%
Aerospace & Defense	jan/80	88	0.94%	147,688	1.02%	1.30%	5.36%	0.24	1,452	1.15	10	1.04%	11.20%
General Industrials	jan/80	172	1.81%	464,725	3.18%	1.32%	4.72%	0.28	2,474	1.97	15	1.53%	8.63%
Electronic & Electrical Equipment	jan/80	561	5.71%	311,497	2.52%	1.29%	6.00%	0.22	499	0.40	81	8.00%	14.09%
Industrial Engineering	jan/80	573	5.89%	351,503	2.71%	1.24%	5.04%	0.25	544	0.43	64	6.76%	11.45%
Industrial Transportation	jan/80	225	2.18%	238,257	1.58%	1.36%	4.76%	0.29	910	0.72	17	1.82%	8.30%
Support Services	jan/80	418	3.94%	280,726	1.76%	1.27%	5.18%	0.25	558	0.44	53	5.11%	12.99%
Consumer Goods													
Automobiles & Parts	jan/80	243	2.39%	461,835	3.73%	1.31%	5.21%	0.25	1,727	1.37	18	1.63%	6.89%
Beverages	jan/80	120	1.23%	273,293	1.70%	1.41%	3.79%	0.37	2,000	1.59	9	0.99%	7.85%
Food Producers	jan/80	374	3.73%	380,964	2.88%	1.44%	3.97%	0.36	911	0.72	32	3.12%	8.40%
Household Goods & Home Construction	jan/80	263	2.75%	206,650	1.44%	1.19%	4.83%	0.25	706	0.56	30	3.23%	11.63%
Leisure Goods	jan/80	151	1.51%	192,317	1.59%	1.31%	5.49%	0.24	1,165	0.93	20	1.93%	12.81%
Personal Goods	jan/80	315	3.06%	244,368	1.56%	1.36%	4.65%	0.29	675	0.54	43	4.21%	13.89%
Tobacco	jan/80	18	0.17%	134,443	0.82%	1.92%	4.99%	0.38	6,350	5.04	0	0.05%	2.51%
Health Care													
Health Care Equipment & Services	jan/80	313	2.79%	277,947	1.48%	1.51%	5.89%	0.26	678	0.54	45	4.11%	15.08%
Pharmaceuticals & Biotechnology	jan/80	371	3.29%	967,168	5.79%	1.79%	6.66%	0.27	2,140	1.70	32	2.81%	8.46%
Consumer Services													
Food & Drug Retailers	jan/80	129	1.30%	226,588	1.40%	1.27%	3.76%	0.34	1,491	1.18	6	0.68%	5.03%
General Retailers	jan/80	454	4.35%	606,665	3.93%	1.40%	4.81%	0.29	1,126	0.89	37	3.82%	8.83%
Media	jan/80	307	2.88%	449,318	2.64%	1.37%	5.67%	0.24	1,175	0.93	33	3.15%	10.99%
Travel & Leisure	jan/80	368	3.52%	377,876	2.46%	1.27%	4.63%	0.27	872	0.69	33	3.29%	9.36%
Telecommunications													
Fixed Line Telecommunications	jan/80	74	0.67%	795,055	5.30%	1.53%	6.37%	0.24	9,800	7.78	4	0.32%	4.73%
Mobile Telecommunications	jan/80	46	0.38%	357,782	1.44%	1.57%	7.33%	0.21	4,791	3.81	2	0.16%	4.16%
Utilities													
Electricity	jan/80	139	1.43%	467,299	3.33%	1.40%	3.61%	0.39	2,965	2.36	3	0.32%	2.29%

Gas, Water & Multiutilities	jan/80	112	1.19%	237,241	1.53%	1.31%	3.24%	0.40	1,831	1.45	4	0.47%	3.76%
Financials													
Banks	jan/80	761	7.19%	1,722,703	10.14%	1.24%	3.73%	0.33	1,851	1.47	69	6.20%	8.49%
Nonlife Insurance	jan/80	176	1.89%	485,078	3.12%	1.38%	4.48%	0.31	2,663	2.12	7	0.81%	4.12%
Life Insurance	jan/80	56	0.62%	216,264	1.11%	1.37%	5.39%	0.25	3,509	2.79	2	0.27%	3.61%
Real Estate Investment & Services	jan/80	270	2.59%	167,454	1.06%	1.22%	4.89%	0.25	510	0.41	23	2.28%	8.77%
Financial Services	jan/80	329	2.85%	515,748	2.86%	1.36%	5.41%	0.25	1,256	1.00	34	3.01%	10.77%
Technology													
Software & Computer Services	jan/80	515	4.03%	597,817	3.21%	1.42%	7.79%	0.18	1,087	0.86	78	6.20%	15.96%
Technology Hardware & Equipment	jan/80	485	4.11%	900,006	4.52%	1.51%	8.01%	0.19	1,368	1.09	56	4.63%	10.98%
Unclassified	jan/80	114	1.65%	38,874	0.63%	1.50%	7.58%	0.20	344	0.27	17	2.67%	12.06%
Total*	jan/80	10,366	100.00%	15,532,281	100.00%	1.34%	4.78%	0.28	1,259	1.00	1,037	100.00%	10.00%

Table 3

Unconditional statistics of the size portfolios: monthly return, migration and delisting

The ten size portfolios are equally-weighted and monthly-rebalanced based on the beginning-of-the-month dollar market capitalization and global breakpoints. The market portfolio is proxied by the TRD World Market Index. *Migration statistics*: every month we counted for each size portfolio the number of firms that stayed in the portfolio, that moved to the +9, +8,…, -8 or -9 portfolio and that disappeared. A firm can disappear from the sample due to delisting (e.g. bankruptcy, merger, acquisition, going private) or filtering (e.g. market capitalization lower than $10 millions). If a firm disappears due to filtering it may reappear if it satisfies the screening rules again. The migration percentages are the total number of migration-type observations (e.g. the stay observations) divided by the total number of migration observations i.e. the sum of the stay, moving and disappear observations. If firms move to another portfolio it is almost always to a neighbour portfolio with roughly equal probability to an upward or downward neighbour. Therefore we did not present the monthly migrations to the more-than-one-portfolio-away portfolios. *Delisting statistics*: TRD registers the status, active or dead, and the date of the last available stock price per firm. We assume that this date is close to the actual delisting date. TRD does not register the reason of delisting. For every dead firm we identified its size portfolio one, five and ten years before its delisting date. The delisting percentages are the number of firms in the x^{th} size portfolio getting delisted next year, in five years or in ten years relative to the total number of firms that get delisted next year, in five years or in ten years.

Size Porfolios	Monthly Return			Migration				Delisting		
	Monthly Return	Standard Deviation	Return/Std	Stay	-1	+1	Disappear	1 year	5 years	10 years
Smallest	3.17	5.55	0.57	79%	0%	9%	12%	11%	12%	12%
2	1.42	5.21	0.27	74%	9%	10%	6%	11%	12%	11%
3	1.18	4.98	0.24	74%	10%	10%	5%	12%	12%	11%
4	1.19	5.02	0.24	75%	11%	10%	3%	11%	11%	11%
5	1.16	4.90	0.24	76%	11%	10%	3%	10%	11%	11%
6	1.13	4.89	0.23	78%	10%	9%	2%	10%	9%	10%
7	1.09	4.83	0.22	81%	9%	8%	2%	9%	10%	9%
8	1.02	4.86	0.21	85%	8%	6%	1%	9%	9%	10%
9	1.01	4.88	0.21	90%	5%	3%	1%	9%	8%	8%
Biggest	0.94	4.67	0.20	96%	3%	0%	1%	6%	7%	7%
Market Portfolio	0.93	4.56	0.20							

Table 4

Average stock exchange distribution (in terms of number of ongoing firms)

The average stock exchange distribution is the time-series average, calculated over the full sample period, of the monthly ratio (in %): number of ongoing firms quoted on the selected stock exchange relative to the total number of ongoing firms, for the pooled sample (column 2) and the sample of the smallest firms (column 3). The larger stock exchanges are defined by having an above-1% weight in the pooled or the smallest firm sample

Stock exchange	Pooled sample	Sample of smallest firms	Sample of smallest firms - Pooled sample
Larger Stock Exchanges			
Alternext US	0.71%	1.09%	0.38%
Athens	1.02%	1.26%	0.24%
Australian	1.30%	0.44%	-0.85%
Bombay	1.95%	1.62%	-0.33%
Euron. Amsterdam	0.70%	1.44%	0.75%
Euronext Paris	1.92%	1.76%	-0.17%
Frankfurt	3.07%	2.63%	-0.44%
Jasdaq	1.77%	2.91%	1.14%
Korea	3.76%	6.99%	3.24%
Kosdaq	1.78%	5.26%	3.48%
London	7.85%	11.07%	3.22%
Milan	1.51%	0.50%	-1.01%
Nasdaq	13.36%	13.82%	0.46%
New York	14.82%	11.14%	-3.68%
NYSE Amex	0.67%	2.45%	1.79%
OTC Bull.Bd.Nasd	1.99%	4.83%	2.84%
Other OTC Nasdaq	4.62%	11.61%	6.99%
Paris-SBF	1.45%	1.08%	-0.37%
Shanghai	1.06%	0.01%	-1.05%
Stockholm	1.09%	1.17%	0.08%
Tokyo	14.49%	1.45%	-13.03%
Toronto	3.97%	3.79%	-0.19%
TSX Venture	0.45%	1.43%	0.98%
Smaller Stock Exchanges			
Alberta	0.01%	0.04%	0.03%
Amsterdam (AEX)	0.33%	0.13%	-0.20%
Amsterdam Unlist	0.00%	0.00%	0.00%
Berlin	0.02%	0.04%	0.01%
Berne	0.00%	0.00%	0.00%
Bogota	0.07%	0.01%	-0.06%
Bordeaux	0.01%	0.01%	0.00%
Brussels	0.31%	0.12%	-0.19%
Brussels Terme	0.07%	0.00%	-0.07%
Buenos Aires	0.12%	0.10%	-0.02%
Bursa Malaysia	0.78%	0.22%	-0.56%
Catalist	0.01%	0.00%	0.00%
Copenhagen	0.77%	0.94%	0.16%
Dublin	0.23%	0.17%	-0.06%
Dusseldorf	0.07%	0.16%	0.08%
Euron. Brussels	0.43%	0.95%	0.52%
Euronext Lisbon	0.19%	0.21%	0.02%
Fukuoka	0.04%	0.03%	-0.02%
Geneva	0.00%	0.00%	0.00%
Hamburg	0.06%	0.09%	0.04%
Hannover	0.01%	0.05%	0.04%
Helsinki	0.50%	0.31%	-0.19%
Hong Kong	0.36%	0.03%	-0.33%
Indonesia SE	0.16%	0.11%	-0.05%
Johannesburg	0.94%	0.27%	-0.68%
Lille	0.01%	0.04%	0.03%
Lima	0.08%	0.06%	-0.01%
Lisbon	0.11%	0.03%	-0.08%

London Plus Mkt	0.00%	0.00%	0.00%
Luxembourg	0.05%	0.03%	-0.02%
Lyon	0.06%	0.19%	0.13%
Madrid	0.03%	0.01%	-0.01%
Madrid-SIBE	0.80%	0.15%	-0.65%
Malaysia 2nd Boa	0.02%	0.02%	-0.01%
Malaysia Mesdaq	0.00%	0.00%	0.00%
Marseilles	0.01%	0.01%	0.00%
Mexico City	0.22%	0.02%	-0.21%
Montreal	0.01%	0.02%	0.01%
Munich	0.12%	0.37%	0.25%
Nagoya	0.16%	0.09%	-0.07%
Nancy	0.01%	0.04%	0.03%
Nantes	0.02%	0.07%	0.05%
Nasdaq Smallcap	0.11%	0.51%	0.40%
National India	0.00%	0.00%	0.00%
New Zealand	0.20%	0.12%	-0.08%
NYSE ARCA	0.02%	0.04%	0.02%
Osaka	0.76%	0.92%	0.16%
Oslo	0.79%	0.61%	-0.19%
Pacific	0.00%	0.00%	0.00%
Philippine SE	0.06%	0.00%	-0.06%
Santiago	0.20%	0.02%	-0.18%
Sao Paulo	0.48%	0.28%	-0.20%
Sapporo	0.01%	0.02%	0.01%
Shenzen	0.81%	0.00%	-0.80%
Singapore	0.46%	0.06%	-0.40%
Singapore OTC	0.01%	0.00%	-0.01%
SIX Swiss	0.83%	0.87%	0.04%
Stuttgart	0.06%	0.12%	0.05%
Swiss SE	0.37%	0.11%	-0.27%
SWX Europe	0.09%	0.00%	-0.09%
Taiwan	0.98%	0.03%	-0.94%
Taiwan OTC	0.21%	0.11%	-0.10%
Thailand	0.59%	0.65%	0.05%
Vienna	0.47%	0.65%	0.18%

Table 5

CAPM-adjusted performance of portfolios classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one months. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. Panel A presents parameter estimates of the Sharpe (1964)-Lintner (1965) asset-pricing model (CAPM)

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \varepsilon_{it},$$

and Panel B reports parameter estimates of the Dimson-beta-adjusted CAPM

$$r_{it} - r_{ft} = a_i + \sum_{-2}^{+2} b_{in}(r_{mt+n} - r_{ft+n}) + \varepsilon_{it},$$

where r_{it} is the return of portfolio *i* in month *t*, r_{ft} is the one-month T-bill rate for month *t*, and r_{mt} the return of the TRD World Market Index (proxy for the market portfolio). Numbers in small case are White's heteroskedasticity-consistent *t*-statistics.

	S	2	3	4	5	6	7	8	9	B
Panel A: Sharpe (1964)-Lintner (1965) asset-pricing model (CAPM)										
$\hat{\alpha}$ (%)	2.32	0.56	0.31	0.30	0.26	0.23	0.18	0.10	0.07	0.01
	10.55	2.99	1.88	1.98	1.96	1.82	1.57	0.98	0.88	0.12
$\hat{\beta}$	0.83	0.87	0.88	0.92	0.93	0.95	0.95	0.99	1.02	1.01
	15.14	17.73	20.35	22.09	26.00	28.48	32.70	39.34	49.63	83.46
Adj. R^2	0.45	0.57	0.63	0.70	0.74	0.77	0.81	0.86	0.90	0.97
Panel B: Dimson-beta-adjusted CAPM										
$\hat{a}$ (%)	2.18	0.42	0.19	0.21	0.21	0.18	0.14	0.07	0.06	0.01
	9.38	2.22	1.15	1.36	1.53	1.39	1.23	0.72	0.72	0.17
$\hat{b}$	0.76	0.81	0.83	0.88	0.91	0.92	0.93	0.97	1.01	1.00
	13.93	16.77	19.23	21.16	24.48	26.92	30.94	37.13	47.98	82.23
$\hat{b}_{t-1}$	0.22	0.20	0.18	0.16	0.11	0.10	0.06	0.06	0.02	0.00
	3.78	4.39	4.63	4.26	3.12	2.97	2.18	2.16	1.02	-0.36
$\hat{b}_{t-2}$	0.03	0.04	0.03	0.00	0.00	-0.01	-0.01	0.00	-0.01	-0.01
	0.44	0.75	0.66	0.00	0.08	-0.29	-0.17	-0.08	-0.55	-0.46
$\hat{b}_{t+1}$	0.00	0.02	0.01	0.02	-0.01	0.01	0.01	0.01	0.00	0.01
	-0.01	0.37	0.29	0.74	-0.25	0.25	0.32	0.29	0.19	0.72
$\hat{b}_{t+2}$	-0.02	-0.01	0.01	0.00	-0.01	0.00	0.00	-0.01	0.00	-0.01
	-0.30	-0.15	0.16	-0.02	-0.39	-0.01	-0.10	-0.52	-0.22	-0.81
Adj. R^2	0.46	0.58	0.64	0.70	0.74	0.77	0.80	0.85	0.89	0.96

Table 6
Descriptive statistics on book-to-market and size portfolios, and missing book values

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their book-to-market value (BtMV) and their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. The book value is missing if it is unknown or non-positive and the corresponding market value is known. All averages are time-series averages of monthly equally-weighted returns, BtMVs and proportions. The return of the firms with missing book values is expressed as the difference with the return of the corresponding size portfolio.

BtMV Portfolios	Return	Size Portfolios	BtMV	Proportion of firms with missing book value[1]	Return of firms with missing book value relative to size portfolio return
L(owest)	0.41%	S(mallest)	1.45	48.19%	-0.03%
2	0.90%	2	1.12	41.16%	-0.69%
3	1.09%	3	0.96	36.76%	-1.01%
4	1.22%	4	0.86	32.83%	-0.91%
5	1.32%	5	0.79	30.14%	-0.73%
6	1.42%	6	0.71	27.38%	-0.57%
7	1.46%	7	0.67	25.65%	-0.55%
8	1.68%	8	0.64	23.04%	-0.50%
9	2.02%	9	0.61	20.51%	-0.46%
H(ighest)	2.91%	B(iggest)	0.55	16.46%	-0.23%

[1] The proportions of firms with missing book value decrease over time for all size portfolios. The average proportion of firms with missing book value for the pooled sample is 30%, ranging from more than 60% in the early 1980s to roughly 5% at the end of the sample period.

Table 7

Fama-French (1993)-adjusted performance of portfolios classified by size model

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. Panel A presents parameter estimates of the Fama-French (1993) model

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \sigma_i SMB_t + \theta_i HML_t + \varepsilon_{it},$$

and Panel B reports parameter estimates of the Fama-French (1993) model adjusted for missing book-values

$$r_{it} - r_{ft} = a_i + b_i(r_{mt} - r_{ft}) + s_i SMB_t^* + h_i HML_t^* + \varepsilon_{it},$$

and Panel C reports parameter estimates of the Fama-French (1993) model adjusted for short-term momentum[1]

$$r_{it} - r_{ft} = A_i + B_i(r_{mt} - r_{ft}) + S_i SMB_t + H_i HML_t + M_i MOM_t + \varepsilon_{it},$$

where r_{it} is the return of portfolio *i* in month *t*, r_{ft} is the one-month T-bill rate for month *t*, and r_{mt} the return of the TRD World Market Index (proxy for the market portfolio). Numbers in small case are White's heteroskedasticity-consistent *t*-statistics. SMB_t and HML_t are calculated according to Fama and French (1993), except for equally weighting, monthly updating and global breakpoints.[2] SMB_t^* and HML_t^* are not calculated from the S/L, S/M, S/H, B/L, B/M, B/H portfolios but directly from (one-dimensionally sorted) size and book-to-market portfolios. Therefore, firms with missing book value do play a role in SMB_t^*, but not in SMB_t. We follow Rouwenhorst (1999) to calculate MOM_t. At the beginning of each month, stocks are sorted in ascending order based on their prior six-month return. Based on each sort, stocks are grouped into two equally-weighted portfolios. The *winners* portfolio contains the 30% highest past performers. The *losers* portfolio contains the 30% lowest past performers. The breakpoints are set globally. The two portfolios are held for six months after portfolio formation. We calculate the monthly average return across six strategies, each starting one month apart to handle the issue of overlapping observations. To attenuate the effect of bid-ask bounce the portfolios are formed one month after the end of the ranking period. MOM_t is then constructed as the monthly profits from buying one dollar of equally weighted *winners* and selling one dollar of equally weighted *losers*.

	S	2	3	4	5	6	7	8	9	B
Panel A: Fama-French (1993) model										
$\hat{\alpha}$ (%)	1.33	-0.33	-0.42	-0.31	-0.17	-0.06	0.02	0.02	0.04	0.02
	9.36	-2.97	-3.68	-2.76	-1.45	-0.44	0.17	0.17	0.42	0.44
$\hat{\beta}$	0.97	0.99	0.98	1.01	0.99	0.99	0.98	1.00	1.02	1.01
	25.55	35.88	39.92	36.42	35.63	33.71	35.09	39.65	47.30	71.57
$\hat{\sigma}$	1.67	1.44	1.21	1.02	0.78	0.56	0.38	0.26	0.14	0.02
	14.38	24.97	20.90	17.90	13.25	9.10	6.49	4.85	3.00	0.65
$\hat{\theta}$	0.15	0.15	0.11	0.09	0.04	0.01	-0.02	-0.03	-0.03	-0.02
	2.28	3.92	2.77	2.53	1.05	0.32	-0.43	-0.93	-0.70	-0.91
Adj. R^2	0.81	0.87	0.87	0.86	0.84	0.83	0.83	0.87	0.90	0.97

[1] This model is also often referenced as the Carhart (1997) model

[2] The Fama-French (1993) methodology and results are well known. It is therefore unnecessary to provide a lengthy review. We simply refer to the Fama and French (1993) paper that provides the corresponding methodology.

Panel B: Fama-French (1993) model adjusted for missing book-values

$\hat{a}$ (%)	1.29	-0.33	-0.42	-0.30	-0.15	-0.05	0.03	0.03	0.04	0.02
	11.48	-3.57	-4.23	-2.74	-1.33	-0.37	0.28	0.27	0.44	0.37
$\hat{b}$	0.99	1.01	0.99	1.02	1.00	0.99	0.98	1.00	1.02	1.01
	36.08	45.50	46.19	38.11	36.55	34.52	35.59	39.88	47.72	72.01
$\hat{s}$	1.79	1.51	1.27	1.04	0.78	0.57	0.38	0.26	0.15	0.04
	19.44	37.40	26.81	20.30	13.74	9.46	6.53	4.83	3.13	1.38
$\hat{h}$	-0.07	-0.04	-0.05	-0.04	-0.05	-0.06	-0.06	-0.07	-0.04	-0.03
	-1.34	-1.38	-1.35	-1.10	-1.22	-1.32	-1.50	-1.67	-1.13	-1.13
Adj. R^2	0.89	0.92	0.91	0.88	0.85	0.83	0.83	0.87	0.90	0.97

Panel C: Fama-French (1993) model adjusted for short-term momentum

$\hat{A}$ (%)	1.45	-0.28	-0.41	-0.30	-0.17	-0.02	0.07	0.06	0.05	0.01
	9.62	-2.36	-3.55	-2.52	-1.45	-0.17	0.57	0.55	0.47	0.12
$\hat{B}$	0.95	0.98	0.97	1.00	0.99	0.98	0.97	0.99	1.02	1.01
	28.56	38.04	40.08	34.94	34.29	32.18	33.97	38.64	46.32	68.55
$\hat{S}$	1.65	1.43	1.21	1.01	0.77	0.55	0.37	0.26	0.14	0.02
	14.62	24.89	20.39	17.44	12.86	8.83	6.31	4.64	2.87	0.70
$\hat{H}$	0.11	0.13	0.11	0.09	0.04	0.00	-0.03	-0.05	-0.03	-0.01
	1.76	3.65	2.85	2.40	0.99	0.01	-0.82	-1.31	-0.81	-0.60
$\hat{M}$	-0.09	-0.04	-0.01	-0.01	-0.01	-0.03	-0.04	-0.04	-0.01	0.02
	-1.20	-0.79	-0.20	-0.31	-0.15	-0.71	-0.87	-0.93	-0.25	0.77
Adj. R^2	0.81	0.87	0.87	0.86	0.84	0.82	0.83	0.87	0.90	0.97

Panel D: Correlation matrix

	HML_t	SMB_t	HML_t^*	SMB_t^*
HML_t	1			
SMB_t	-0.099	1		
HML_t^*	0.981	0.085	1	
SMB_t^*	0.130	0.897	0.301	1

Table 8

Geographical and sectorial distribution and proportions of the missing-book-value firms

The book value is missing if it is unknown or non-positive and the corresponding market value is known. *Distribution* is the time-series average of the monthly ratio (in %): number of missing-book-value firms relative to the total number of missing-book firms. *Proportion* is the time-series average of the monthly ratio (in %): number of missing-book-value firms relative to the number of ongoing firms in the country or sector

Country	Distribution	Proportion	Sector	Distribution	Proportion
Developed markets			*Oil & Gas*		
Australia	0.83%	27.93%	Oil & Gas Producers	3.08%	34.11%
Austria	0.47%	34.93%	Oil Equipment, Services & Distribution	0.85%	25.58%
Belgium	1.57%	53.15%	Alternative Energy	0.17%	29.65%
Canada	7.76%	43.77%	*Basic Materials*		
Denmark	0.75%	35.54%	Chemicals	3.13%	25.27%
Finland	0.22%	16.81%	Forestry & Paper	0.69%	23.92%
France	3.12%	25.45%	Industrial Metals & Mining	1.93%	26.06%
Germany	3.37%	36.39%	Mining	3.30%	48.36%
Greece	1.01%	36.08%	*Industrials*		
Hong Kong	0.35%	44.34%	Construction & Materials	3.87%	23.87%
Ireland	0.33%	39.91%	Aerospace & Defense	0.56%	17.35%
Italy	2.07%	50.43%	General Industrials	1.73%	30.51%
Japan	8.60%	21.17%	Electronic & Electrical Equipment	6.09%	31.47%
Luxembourg	0.13%	47.69%	Industrial Engineering	5.11%	27.13%
Netherlands	0.59%	13.70%	Industrial Transportation	1.69%	26.07%
New Zealand	0.15%	33.91%	Support Services	3.51%	27.95%
Norway	0.64%	28.20%	*Consumer Goods*		
Portugal	0.18%	16.58%	Automobiles & Parts	2.17%	26.80%
Singapore	0.63%	45.90%	Beverages	1.16%	30.04%
Spain	0.61%	26.17%	Food Producers	3.17%	28.09%
Sweden	0.84%	26.76%	Household Goods & Home Construction	2.26%	24.39%
Switzerland	1.60%	39.61%	Leisure Goods	1.54%	27.14%
U.K.	2.43%	6.61%	Personal Goods	2.75%	27.68%
U.S.	40.48%	32.74%	Tobacco	0.15%	20.14%
Emerging Markets			*Health Care*		
Argentina	0.12%	24.62%	Health Care Equipment & Services	2.72%	32.06%
Brazil	0.33%	14.67%	Pharmaceuticals & Biotechnology	4.05%	35.45%
Chili	0.10%	16.28%	*Consumer Services*		
China	2.16%	42.87%	Food & Drug Retailers	0.87%	22.16%
Colombia	0.06%	14.41%	General Retailers	3.27%	25.07%
India	2.63%	39.64%	Media	3.56%	31.24%
Indonesia	0.18%	17.45%	Travel & Leisure	3.43%	30.99%
Korea	11.50%	46.42%	*Telecommunications*		
Malaysia	0.61%	45.99%	Fixed Line Telecommunications	0.90%	33.20%
Mexico	0.20%	23.06%	Mobile Telecommunications	0.49%	25.48%
Peru	0.09%	26.70%	*Utilities*		
Philippines	0.04%	26.17%	Electricity	0.97%	20.05%
South Africa	1.47%	53.68%	Gas, Water & Multiutilities	0.78%	20.51%
Taiwan	1.27%	38.40%	*Financials*		
Thailand	0.49%	24.57%	Banks	8.66%	41.06%
			Nonlife Insurance	2.06%	35.52%
			Life Insurance	0.56%	29.92%
			Real Estate Investment & Services	3.42%	39.60%
			Financial Services	4.53%	44.02%
			Technology		
			Software & Computer Services	4.77%	32.23%
			Technology Hardware & Equipment	4.28%	23.41%
			Unclassified	1.76%	39.37%
Total***	100.00%	30.20%	Total***	100.00%	30.20%

Table 9

Short-term momentum and the size portfolios

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. We follow Rouwenhorst (1999) to calculate the momentum (MOM) portfolios. At the beginning of each month, stocks are sorted in ascending order based on their prior six-month return. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for six months after portfolio formation. We calculate the monthly average return across six strategies, each starting one month apart to handle the issue of overlapping observations. To attenuate the effect of bid-ask bounce the portfolios are formed one month after the end of the ranking period. *Losers* denotes the worst 10% past performers, *Winners* denotes the 10% best past performers. *HP*6*m* is the time-series average of the monthly six-month holding period return. *P*6*m* is the time-series average of the monthly six-month past return.

MOM Portfolios	*HP*6*m*	Size Portfolios	*P*6*m*
Losers	0.99%	Smallest	0.19%
2	0.98%	2	1.35%
3	1.06%	3	1.64%
4	1.13%	4	1.73%
5	1.21%	5	1.81%
6	1.28%	6	1.94%
7	1.35%	7	1.93%
8	1.45%	8	2.02%
9	1.56%	9	1.89%
Winners	1.64%	Biggest	1.82%

Table 10

Liquidity portfolios and the size portfolios

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization, and their illiquidity measure *ILL*12. Based on each sort, stocks are grouped into equally-weighted size decile portfolios and equally-weighted liquidity decile portfolios, based on global breakpoints. The liquidity decile portfolios are held for six months after portfolio formation. We calculate the monthly average return across six strategies, each starting one month apart to handle the issue of overlapping observations. *HP*6*m* is the time-series average of the monthly six-month holding period return. As a measure of illiquidity, we use the zero-return proportion proposed by Lesmond *et al.* (1999) i.e. the monthly proxy for illiquidity, *ILL*1, is calculated as the ratio of the number of zero-return days to the number of trading days in a given month.[1] *ILL*12 is the average *ILL*1 over the prior 12 months. The *ILL*12 measure, reported here, is the time-series average of the monthly average *ILL*12. Before May 1988 the dispersion of the illiquidity measure *ILL*12 was quite small.[2] Therefore, we calculate liquidity statistics from May 1988 till May 2009. $\widehat{\alpha}$ and $\hat{\beta}$ are the parameter estimates of the Sharpe (1964)-Lintner (1965) asset-pricing model (CAPM)

$$r_{it} - r_{ft} = \alpha_i + \beta_i\left(r_{mt} - r_{ft}\right) + \varepsilon_{it},$$

where r_{it} is the return of liquidity portfolio *i* in month *t*, r_{ft} is the one-month T-bill rate for month *t*, and r_{mt} the return of the TRD World Market Index (proxy for the market portfolio). *Firm size* is the time-series average of the monthly average firm market capitalization. *Smallest firms* have a market capitalization in the first size decile of the pooled sample. Size breakpoints are updated monthly. *Distribution* is the time-series average of the monthly ratio (in %): number of smallest stocks relative to the total number of smallest stocks.

LIQ Portfolios	*ILL*12	*HP*6m	$\hat{\beta}$	$\widehat{\alpha}$	Firm size	Distribution of smallest stocks	Size Portfolios	*ILL*12
Liquid	0.02	0.98	1.11	0.25	5,429	1.88%	Smallest	0.31
2	0.05	0.70	1.16	-0.05	3,769	1.81%	2	0.29
3	0.08	0.75	1.12	0.02	2,330	3.33%	3	0.27
4	0.10	0.78	1.04	0.08	1,558	4.93%	4	0.24
5	0.13	0.91	0.96	0.24	1,053	6.95%	5	0.21
6	0.16	1.08	0.88	0.43	646	9.78%	6	0.18
7	0.20	1.19	0.83	0.56	405	13.84%	7	0.15
8	0.26	1.24	0.74	0.65	301	18.30%	8	0.12
9	0.37	1.21	0.66	0.64	247	17.89%	9	0.10
Illiquid	0.63	1.28	0.55	0.75	166	21.29%	Biggest	0.07

[1] It is important to exclude non-trading days from the sample because TRD fills a non-trading day with the total return index of the prior trading day, a process that inflates zero-return proportions. For example, Lee (2010) identifies a non-trading day if more than 90% of stocks in a given exchange have zero returns on that day. Although it is possible to download the monthly number of zero returns directly from TRD, following Lee (2010) in correcting for non-trading days would still require downloading daily data, which can be quite cumbersome for large datasets. We, therefore, identify the monthly non-trading days as the number of zero returns of the local index of a given exchange. The list of local indices is in Appendix A. We tested the reliability of this approach on a subsample of countries by comparing the zero daily local index returns: (i) with other third-party country indices (we found the local indices more reliable than third-party indices for this purpose); (ii) with internet resources on stock exchange holidays such as the exchange's website; (iii) with the daily returns of a subsample of large companies on the exchange; (iv) with, if available, the VACS datatype in TRD which returns the stock exchange non-trading days. In case of multiple stock exchanges in one country we found no example of non-synchronic non-trading days, such that the local index suits for all exchanges in a country.

[2] Before May 1988 stocks with an *ILL*12 measure of zero occupied more than one decile liquidity portfolio.

Table 11

Liu (2006) liquidity-adjusted performance of portfolios classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. Panel A presents parameter estimates of the Lui (2006) liquidity-augmented CAPM

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \lambda_i LIQ_t + \varepsilon_{it},$$

and Panel B reports parameter estimates of the Liu (2006) liquidity-augmented Fama-French (1993) model,

$$r_{it} - r_{ft} = a_i + b_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + l_i LIQ_t + \varepsilon_{it},$$

where r_{it} is the return of portfolio *i* in month *t*, r_{ft} is the one-month T-bill rate for month *t*, and r_{mt} the return of the TRD World Market Index (proxy for the market portfolio). Numbers in small case are White's heteroskedasticity-consistent *t*-statistics. SMB_t and HML_t are calculated according to Fama and French (1993), except for equally weighting, monthly updating and global breakpoints.[1] We follow Liu (2006) to calculate LIQ_t. At the beginning of each month, stocks are sorted in ascending order based on their illiquidity measure $ILL12$. Based on each sort, stocks are grouped into two equally-weighted portfolios. The high-illiquidity portfolio contains the 30% highest illiquidity stocks. The low-illiquidity portfolio contains the 30% lowest illiquidity stocks. The breakpoints are set globally. The two portfolios are held for six months after portfolio formation. We calculate the monthly average return across six strategies, each starting one month apart to handle the issue of overlapping observations. LIQ_t is then constructed as the monthly profits from buying one dollar of equally weighted high-illiquidity and selling one dollar of equally weighted low-illiquidity. We follow Lee (2011) to calculate the illiquidity measure $ILL12$. The monthly proxy for illiquidity, $ILL1$, is calculated as the ratio of the number of zero-return days to the number of trading days in a given month.[2] $ILL12$ is the average $ILL1$ over the prior 12 months. Before May 1988 the dispersion of the illiquidity measure $ILL12$ was quite small.[3] Therefore, we apply the liquidity-augmented models from May 1988 till May 2009.

	Smallest	2	3	4	5	6	7	8	9	Biggest
Panel A: Liu (2006) liquidity-augmented CAPM										
$\hat{\alpha}$ (%)	2.43	0.61	0.33	0.33	0.27	0.23	0.16	0.11	0.08	0.01
	8.46	2.67	1.67	1.83	1.65	1.49	1.16	0.89	0.79	0.30
$\hat{\beta}$	0.88	0.91	0.91	0.95	0.94	0.94	0.96	0.98	1.01	1.02
	12.69	15.17	16.77	18.20	19.83	20.28	22.78	27.59	35.05	81.64

[1] The Fama-French (1993) methodology and results are well known. It is therefore unnecessary to provide a lengthy review. We simply refer to the Fama and French (1993) paper that provides the corresponding methodology.

[2] It is important to exclude non-trading days from the sample because TRD fills a non-trading day with the total return index of the prior trading day, a process that inflates zero-return proportions. Lee (2011) identifies a non-trading day if more than 90% of stocks in a given exchange have zero returns on that day. Although it is possible to download the monthly number of zero returns directly from TRD, following Lee (2011) in correcting for non-trading days would still require downloading daily data, which can be quite cumbersome for large datasets. We, therefore, identify the monthly non-trading days as the number of zero returns of the local index of a given exchange. The list of local indices is in Table 25. We tested the reliability of this approach on a subsample of countries by comparing the zero daily local index returns: (i) with other third-party country indices (we found the local indices more reliable than third-party indices for this purpose); (ii) with internet resources on stock exchange holidays such as the exchange's website; (iii) with the daily returns of a subsample of large companies on the exchange; (iv) with, if available, the VACS datatype in TRD which returns the stock exchange non-trading days. In case of multiple stock exchanges in one country we found no example of non-synchronic non-trading days, such that the local index suits for all exchanges in a country.

[3] Before May 1988 stocks with an $ILL12$ measure of zero occupied more than one decile liquidity portfolio.

$\hat{\lambda}$	0.18	0.22	0.19	0.17	0.09	0.04	0.02	-0.01	-0.02	0.00
	1.52	2.32	2.38	2.31	1.36	0.74	0.34	-0.33	-0.60	0.28
Adj. R^2	0.46	0.57	0.64	0.71	0.76	0.78	0.82	0.87	0.91	0.98
Panel B: Liu (2006) liquidity-augmented Fama-French (1993) model										
$\hat{a}$ (%)	1.30	-0.33	-0.46	-0.31	-0.20	-0.10	-0.03	-0.01	-0.03	-0.01
	9.07	-2.82	-3.94	-2.42	-1.47	-0.64	-0.18	-0.05	-0.25	-0.17
$\hat{b}$	0.99	1.00	0.99	1.01	0.98	0.97	0.98	0.99	1.02	1.02
	24.31	31.93	35.89	29.61	27.42	23.73	24.83	28.93	36.51	79.99
$\hat{s}$	1.78	1.50	1.26	1.02	0.74	0.52	0.35	0.23	0.12	0.02
	15.40	24.22	20.01	14.58	10.56	6.90	4.67	3.47	2.11	0.61
$\hat{h}$	0.29	0.23	0.20	0.16	0.12	0.08	0.03	0.02	0.04	0.01
	5.93	5.84	5.24	4.16	2.87	1.75	0.76	0.39	1.11	0.68
$\hat{l}$	-0.13	-0.04	-0.02	0.00	-0.04	-0.05	-0.04	-0.05	-0.04	0.00
	-1.90	-1.00	-0.60	-0.02	-0.65	-0.80	-0.74	-1.14	-1.15	0.07
Adj. R^2	0.85	0.90	0.89	0.87	0.84	0.82	0.84	0.87	0.91	0.98

Table 12
Business cycle-adjusted performance of portfolios classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. Panel A presents parameter estimates of the CAPM augmented with Chan et al. (1985)'s measure of the changing risk premium,

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \pi_i PREM_t + \varepsilon_{it},$$

and Panel B reports parameter estimates of the Fama-French (1993) model augmented with Chan et al. (1985)'s measure of the changing risk premium,

$$r_{it} - r_{ft} = a_i + b_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + p_i PREM_t + \varepsilon_{it},$$

where r_{it} is the return of portfolio *i* in month *t*, r_{ft} is the one-month T-bill rate for month *t*, and r_{mt} the return of the TRD World Market Index (proxy for the market portfolio). Numbers in small case are White's heteroskedasticity-consistent *t*-statistics. SMB_t and HML_t are calculated according to Fama and French (1993), except for equally weighting, monthly updating and global breakpoints.[1] We follow Chan et al. (1985) to measure the changing risk premium by measuring the behavior of bonds of different perceived riskiness. $PREM_t$ is the difference the return on a portfolio of "junk" bonds and the return on a portfolio of long-term government bonds.[2] The variable $PREM_t$ is intended to capture changes in the expected premium on risky assets.[3]

	S	2	3	4	5	6	7	8	9	B
Panel A: CAPM augmented with Chan et al. (1985)'s measure of the changing risk premium										
$\hat{\alpha}$ (%)	2.37	0.61	0.35	0.34	0.29	0.26	0.20	0.12	0.09	0.01
	11.16	3.45	2.26	2.37	2.30	2.14	1.83	1.22	1.08	0.18
$\hat{\beta}$	0.75	0.79	0.81	0.87	0.88	0.90	0.92	0.96	1.00	1.00
	14.30	18.25	20.77	22.94	26.88	29.40	33.37	40.73	49.54	85.18
$\hat{\pi}$	0.35	0.34	0.28	0.26	0.21	0.19	0.15	0.13	0.09	0.02
	4.08	4.57	4.61	4.65	4.93	4.58	4.55	4.23	3.23	1.30
Adj. R^2	0.49	0.61	0.67	0.72	0.76	0.79	0.82	0.86	0.90	0.97
Panel B: Fama-French (1993) model augmented with Chan et al. (1985)'s measure of the changing risk premium										
$\hat{\alpha}$ (%)	1.35	-0.29	-0.39	-0.27	-0.13	-0.01	0.06	0.06	0.07	0.03
	9.81	-2.61	-3.40	-2.47	-1.15	-0.09	0.51	0.53	0.77	0.60

[1] The Fama-French (1993) methodology and results are well known. It is therefore unnecessary to provide a lengthy review. We simply refer to the Fama and French (1993) paper that provides the corresponding methodology.
[2] The portfolio of "junk" bonds is instrumented by the BofA Merrill Lynch US High Yield 100 Index (H100) and the portfolio of long-term government bonds by the Bofa Merrill Lynch 10+ Year US Treasury Index (G9O2). Although this is an international study, we preferred US indices because government bonds of low-rated countries are not a good proxy for the long-term riskless asset. We did not have access to sufficient historical data from other high-quality providers. Further details on the indices can be found on http://www.mlindex.ml.com
[3] Chan et al. (1985) hypothise that the risk premium may change as a result of changing business conditions i.e. the business cycle

$\hat{\beta}$	0.96	0.97	0.96	0.99	0.97	0.96	0.95	0.98	1.00	1.00
	24.00	35.68	38.94	36.00	35.08	33.32	34.74	40.05	45.59	69.54
$\hat{s}$	1.64	1.40	1.17	0.98	0.74	0.51	0.34	0.22	0.11	0.01
	13.34	23.23	19.50	16.82	12.12	8.04	5.55	3.93	2.18	0.35
$\hat{h}$	0.06	0.23	0.20	0.16	0.12	0.08	0.03	0.02	0.04	0.01
	2.23	3.85	2.68	2.45	0.94	0.19	-0.55	-1.04	-0.80	-0.95
$\hat{p}$	0.07	0.10	0.08	0.09	0.08	0.11	0.09	0.09	0.07	0.02
	1.34	2.64	2.52	2.76	2.85	3.09	3.09	3.25	2.61	1.16
Adj. R^2	0.81	0.88	0.87	0.86	0.85	0.83	0.84	0.87	0.90	0.97

Table 13

January seasonal and the size portfolios

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month.

Size Portfolios	January return	non-January return	Difference
Smallest	8.40	2.68	5.71
2	5.16	1.07	4.09
3	4.26	0.89	3.37
4	3.55	0.97	2.57
5	2.69	1.02	1.67
6	2.45	1.01	1.44
7	1.99	1.00	0.99
8	1.70	0.96	0.74
9	1.29	0.98	0.31
Biggest	0.78	0.95	-0.18

Table 14

The January-adjusted performance of portfolios classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. Panel A presents parameter estimates of the CAPM extended with a January dummy, D_t,

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \mu_i D_t + \varepsilon_{it},$$

And Panel B presents parameter estimates of the Fama-French (1993) model extended with a January dummy, D_t,

$$r_{it} - r_{ft} = a_i + b_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + m_i D_t + \varepsilon_{it},$$

where r_{it} is the return of portfolio *i* in month *t*, r_{ft} is the one-month T-bill rate for month *t*, and r_{mt} the return of the TRD World Market Index (proxy for the market portfolio). Numbers in small case are White's heteroskedasticity-consistent *t*-statistics. SMB_t and HML_t are calculated according to Fama and French (1993), except for equally weighting, monthly updating and global breakpoints.[1] D_t is the January dummy variable.

	S	2	3	4	5	6	7	8	9	B
Panel A: January-adjusted CAPM										
$\hat{\alpha}$ (%)	1.83	0.21	0.02	0.08	0.12	0.11	0.09	0.03	0.05	0.02
	9.47	1.17	0.14	0.53	0.88	0.84	0.80	0.33	0.55	0.44
$\hat{\beta}$	0.83	0.87	0.87	0.92	0.93	0.95	0.95	0.99	1.02	1.01
	15.59	18.23	20.73	22.56	26.25	28.76	32.88	39.42	49.65	83.70
$\hat{\mu}$	5.71	4.09	3.37	2.57	1.66	1.43	0.98	0.73	0.30	-0.19
	5.06	5.40	5.55	4.79	3.52	2.96	2.47	2.14	0.98	-1.40
Adj. R^2	0.53	0.61	0.67	0.72	0.75	0.78	0.81	0.86	0.90	0.97
Panel B: January-adjusted Fama-French (1993) model										
$\hat{a}$ (%)	1.24	-0.36	-0.44	-0.31	-0.15	-0.06	0.01	0.01	0.04	0.04
	8.68	-3.17	-3.83	-2.77	-1.32	-0.48	0.12	0.10	0.43	0.66
$\hat{b}$	0.96	0.99	0.98	1.01	0.99	0.99	0.98	1.00	1.02	1.01
	24.82	35.06	39.11	35.87	35.63	33.27	34.75	39.24	47.10	71.63
$\hat{s}$	1.58	1.42	1.19	1.02	0.79	0.56	0.37	0.25	0.14	0.03
	14.86	23.76	19.09	16.60	12.64	8.67	5.98	4.33	2.83	0.98
$\hat{h}$	0.13	0.14	0.11	0.09	0.05	0.01	-0.02	-0.04	-0.03	-0.02
	1.97	3.69	2.62	2.45	1.10	0.29	-0.45	-0.96	-0.69	-0.80
$\hat{m}$	1.80	0.55	0.41	0.04	-0.27	0.09	0.11	0.17	-0.02	-0.24
	3.30	1.55	1.18	0.11	-0.71	0.22	0.29	0.48	-0.06	-1.57
Adj. R^2	0.82	0.87	0.87	0.86	0.84	0.82	0.83	0.87	0.90	0.97

[1] The Fama-French (1993) methodology and results are well known. It is therefore unnecessary to provide a lengthy review. We simply refer to the Fama and French (1993) paper that provides the corresponding methodology.

Table 15

Currency distribution in the pooled and the smallest firm sample

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one months. The *smallest firm sample* denotes the smallest decile portfolio. The *currency distribution* is the time-series average, calculated over the full sample period, of the monthly ratio (in %): number of ongoing firms quoted in the particular currency relative to the total number of ongoing firms.

We do not have historical data on the currency denomination of the stocks. We only have the last known currency denomination of the delisted stocks and the current currency denomination of the ongoing stocks. This is a potential issue for the pre-euro period of the ongoing euro-stocks or euro-stocks delisted after joining the euro. For these stocks we do not have the historical pre-euro currency denomination. However, we do know on which stock exchange these stocks were/are listed; and we used this information to deduct the pre-euro currency denomination of these stocks.

All proxies for the short-term risk-free interest rate are downloaded from TRD, except for the U.S. one-month T-Bill rate which is downloaded from Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

k^{th}	Currency name	Code	Pooled sample	Smallest firm sample	Difference	Risk-free rate
1	Australian dollar	AUD	1.13%	0.41%	-0.72%	Australia dealer bill 90 day - middle rate
2	Canadian dollar	CAD	4.08%	5.16%	1.08%	Canada treasury bill auction 3 month - middle rate
3 (pre-euro)	German mark*	DEM	2.36%	2.00%	-0.36%	Germany public bond outstanding - red. Yield
3 (post-euro)	Euro	EUR	4.36%	3.74%	-0.62%	Euribor 3 month - offered rate
4	British pound	GBP	9.26%	11.10%	1.83%	Uk 3 months treasury bills yield (ep)
5	Japanese yen	JPY	16.88%	5.62%	-11.26%	Basic discount & loan rate - middle rate
6	Korean won	KRW	4.72%	12.55%	7.83%	Korea ncd 91 days - middle rate
7	South African rand	ZAR	0.97%	0.27%	-0.70%	Sa t-bill 91 days (tender rates) - red. Yield
8	Argentine peso	ARS	0.13%	0.10%	-0.04%	Argentina interbank 7 d (pa.) - middle rate
9	Austrian schilling*	ATS	0.34%	0.57%	0.23%	Austrian bond yield central govt - red. Yield
10	Belgian franc*	BEF	0.62%	0.94%	0.32%	Belgium treasury bill3mth'dead' - middle rate
11	Brazilian real	BRL	0.35%	0.28%	-0.07%	Brazil selic target rate - middle rate
12	Chilean peso	CLP	0.16%	0.02%	-0.15%	Chile repo 7 day - middle rate
13	Chinese yuan	CNY	1.41%	0.01%	-1.40%	China relending rate, 3m - middle rate
14	Colombian peso	COP	0.03%	0.00%	-0.03%	Colombia interbank overnight - middle rate
15	Danish krone	DKK	0.77%	0.94%	0.17%	Denmark lending rate - middle rate
16	Dutch guilder*	NLG	0.88%	1.42%	0.54%	Netherland interbank 1 mth - middle rate
17	Finnish mark*	FIM	0.18%	0.18%	0.00%	Finland interbank fixing 1 month - offered rate
18	French franc*	FRF	2.30%	1.95%	-0.34%	Franceinterbank call (tmp) - offered rate
19	Greek drachma*	GRD	0.31%	0.57%	0.27%	Greece treasury bill 3 month - middle rate
20	Hong Kong dollar	HKD	0.35%	0.01%	-0.34%	Hkd depo 1 month - middle rate
21	Indian rupee	INR	1.52%	1.62%	0.10%	India t-bill secondary 91 day - red. Yield
22	Indonesian rupiah	IDR	0.15%	0.11%	-0.04%	Indonesia sbi/disc 90 day'dead' - middle rate
23	Irish pound*	IEP	0.17%	0.17%	0.00%	Ireland interbank 1 month - offered rate
24	Italian lira*	ITL	0.98%	0.34%	-0.64%	Italy t-bill auct. Gross 3 month - middle rate
25	Luxembourgian franc*	LUF	0.02%	0.03%	0.01%	Belgium treasury bill3mth'dead' - middle rate
26	Malaysian ringgit	MYR	0.74%	0.23%	-0.50%	Malaysia t-bill band 4 - middle rate
27	Mexican peso	MXN	0.19%	0.02%	-0.17%	Mexico cetes 2nd mkt. 28 day - middle rate
28	New Zealand dollar	NZD	0.16%	0.12%	-0.05%	New zealand 3 month t-bill 'dead' - middle rate
29	Norwegian krone	NOK	0.74%	0.61%	-0.13%	Norway interbank 3 month - offered rate
30	Peruvian Nuevo Sol	PEN	0.06%	0.06%	0.01%	Peru legal interes (nuevos soles) - middle rate
31	Philippine peso	PHP	0.05%	0.00%	-0.05%	Philippine treasury bill 91d - middle rate
32	Portuguese escudo*	PTE	0.17%	0.20%	0.03%	Portugal td3 - middle rate
33	Singapore dollar	SGD	0.50%	0.06%	-0.45%	Singapore t-bill 3 month - middle rate
34	Spanish peseta*	ESP	0.44%	0.13%	-0.31%	Spain interbank w/a 1 month - middle rate
35	Swedish krona	SEK	1.04%	1.19%	0.15%	Sweden repo 1 month'dead' - middle rate
36	Swiss franc	CHF	1.41%	0.97%	-0.44%	Swiss liq.financing rate (snb) - middle rate
37	Taiwan dollar	TWD	0.99%	0.15%	-0.84%	Taiwan money market 90 day - middle rate
38	Thai baht	THB	0.58%	0.65%	0.07%	Thailand repo 3 mth'dead' - middle rate
39	American dollar	USD	38.50%	45.50%	7.00%	U.S. one-month T-Bill rate

* These currencies joined the Euro on January 1, 1999, except for the Greek drachma that joined the euro on January 1, 2001. Slovenia (January 1, 2007), Cyprus and Malta (January 1, 2008) are not included in the dataset.

Table 16

Sercu (1980) exchange risk-adjusted performance of portfolios classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. Panel A presents parameter estimates of the adjusted Sercu (1980) international CAPM

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \sum_{k=1}^{7} \psi_{ik} XF_{kt} + \varsigma_i CXF_{it} + \varepsilon_{it},$$

and Panel B reports parameter estimates of the adjusted Sercu (1980) international Fama-French (1993) model,

$$r_{it} - r_{ft} = a_i + b_i(r_{mt} - r_{ft}) + \sum_{k=1}^{7} p_{ik} XF_{kt} + g_i CXF_{it} + s_i SMB_t + h_i HML_t + \varepsilon_{it},$$

$$\text{with } XF_{kt} = s_{kt} + r_{ft}^k - r_{ft},$$

$$\text{with } CXF_{it} = \sum_{k=8}^{38} \omega_{it}^k XF_{kt} \text{ and } \omega_{it}^k = \frac{n_{it}^k}{\sum_{k=8}^{38} n_{it}^k}$$

where r_{it} is the return of portfolio *i* in month *t*, r_{ft} is the one-month U.S. T-Bill rate for month *t* (downloaded from Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/); r_{mt} the return of the TRD World Market Index (as proxy for the market portfolio); XF_{kt} the k^{th} exchange factor for month *t* where *k* denotes the k^{th} currency (see Table 13, for the k^{th} currency); s_{kt} is the percentage change of the k^{th} exchange rate (against the USD)[1] for month *t*, r_{ft}^k is the proxy for the k^{th} one-month risk-free interest rate (see Table 13, for the proxy of the one-month risk-free interest rate associated with the k^{th} currency); CXF_{it} is the compounded exchange factor tailored for the i^{th} size decile which is calculated as the weighted average of the other exchange factors weighted by the number of stocks denominated in the k^{th} currency in decile *i* at time *t*, or n_{it}^k. If XF_{kt} is missing, due to an unavailable r_{ft}^k, we set XF_{kt} equal to s_{kt} to avoid an undesired reduction of the regression period.[2] SMB_t and HML_t are calculated according to Fama and French (1993), except for equally weighting, monthly updating and global breakpoints.[3] Numbers in small case are White's heteroskedasticity-consistent *t*-statistics.

	S	2	3	4	5	6	7	8	9	B
Panel A: Adjusted Sercu (1980) international CAPM										
$\hat{\alpha}$ (%)	2.40	0.60	0.33	0.31	0.27	0.24	0.18	0.11	0.07	0.00
	10.81	3.26	2.08	2.03	2.04	1.92	1.62	1.08	0.89	0.05
$\hat{\beta}$	0.73	0.80	0.80	0.86	0.86	0.89	0.90	0.94	0.98	1.01
	11.84	13.22	14.61	15.36	18.35	20.31	23.29	28.67	35.64	71.46
$\hat{\psi}_{AUD}$	0.04	0.03	0.08	0.08	0.04	0.04	0.03	0.02	0.03	0.01
	0.46	0.44	1.26	1.41	0.81	0.79	0.75	0.46	0.94	0.50
$\hat{\psi}_{CAD}$	0.24	0.24	0.21	0.21	0.21	0.19	0.17	0.15	0.11	0.04
	1.77	2.09	2.08	2.13	2.59	2.34	2.22	2.23	1.97	1.26
$\hat{\psi}_{DEM-EUR}$	-0.55	-0.35	-0.28	-0.13	-0.07	-0.12	-0.08	-0.06	-0.05	0.04
	-2.64	-2.16	-2.08	-1.02	-0.60	-1.11	-0.86	-0.86	-0.77	1.00
$\hat{\psi}_{GBP}$	-0.08	-0.07	-0.08	-0.08	-0.11	-0.09	-0.07	-0.07	-0.07	-0.05
	-0.79	-0.77	-1.09	-1.17	-1.75	-1.54	-1.44	-1.59	-1.83	-2.53
$\hat{\psi}_{JPY}$	-0.18	-0.16	-0.12	-0.10	-0.07	-0.06	-0.05	-0.04	-0.03	-0.04

[1] To maximize the availability, exchange rates are first downloaded from TRD as WM/Reuters rates against GBP and, then, converted against USD using the WM/Reuters USD/GBP exchange rate.

[2] Setting XF_{kt} equal to s_{kt} assumes that $r_{ft}^k = r_{ft}$, which is generally not the case. The alternative is setting XF_{kt} equal to zero, which assumes that, under CIP, the forward rate perfectly predicts the future spot rate, which is empirically massively rejected. We applied both and the results are comparable. However, we do have a preference for setting XF_{kt} equal to s_{kt} as r_{ft} is the leading interest rate of other currencies and, therefore, most of the variability of XF_{kt} comes from the variability in s_{kt}

[3] The Fama-French (1993) methodology and results are well known. It is therefore unnecessary to provide a lengthy review. We simply refer to the Fama and French (1993) paper that provides the corresponding methodology.

	-2.57	-2.62	-2.12	-1.93	-1.36	-1.34	-1.36	-1.26	-1.09	-2.78
$\hat{\psi}_{KRW}$	0.25	0.23	0.17	0.12	0.10	0.06	0.05	0.03	0.01	0.00
	3.21	3.00	2.48	1.96	1.99	1.17	1.26	0.91	0.39	-0.19
$\hat{\psi}_{ZAR}$	0.07	0.03	0.03	0.03	0.05	0.05	0.04	0.04	0.03	0.00
	1.20	0.73	0.70	0.76	1.44	1.43	1.22	1.82	1.30	0.25
$\hat{\varsigma}$	0.54	0.30	0.26	0.14	0.13	0.23	0.20	0.16	0.13	0.01
	2.19	1.50	1.46	0.77	0.79	1.55	1.56	1.68	1.56	0.16
Adj. R^2	0.51	0.61	0.67	0.72	0.76	0.78	0.82	0.86	0.90	0.97
Panel B: Adjusted Sercu (1980) international Fama-French (1993) model										
$\hat{a}$ (%)	1.43	-0.28	-0.38	-0.30	-0.14	-0.03	0.05	0.06	0.06	0.03
	9.43	-2.53	-3.49	-2.64	-1.19	-0.24	0.43	0.51	0.65	0.52
$\hat{b}$	0.93	0.98	0.95	0.98	0.95	0.94	0.93	0.95	0.99	1.00
	22.53	31.04	31.25	26.56	26.06	24.11	24.56	28.08	33.44	57.28
$\hat{s}$	1.61	1.40	1.18	1.01	0.77	0.55	0.36	0.24	0.13	0.01
	13.88	24.81	21.34	18.15	13.60	9.03	6.36	4.62	2.78	0.36
$\hat{h}$	0.13	0.13	0.09	0.08	0.03	0.00	-0.03	-0.05	-0.04	-0.02
	1.96	3.67	2.39	2.23	0.63	0.01	-0.87	-1.40	-1.00	-1.02
$\hat{p}_{AUD}$	-0.01	-0.01	0.05	0.05	0.03	0.03	0.03	0.02	0.03	0.01
	-0.15	-0.19	1.27	1.40	0.63	0.63	0.74	0.56	1.05	0.68
$\hat{p}_{CAD}$	0.14	0.16	0.15	0.15	0.17	0.16	0.15	0.14	0.10	0.04
	1.63	2.25	2.25	2.21	2.58	2.27	2.14	2.18	1.91	1.30
$\hat{p}_{DEM-EUR}$	-0.18	0.01	0.05	0.11	0.10	0.02	0.01	-0.01	-0.02	0.04
	-1.46	0.17	0.72	1.37	1.18	0.19	0.10	-0.15	-0.36	1.08
$\hat{p}_{GBP}$	-0.19	-0.16	-0.15	-0.15	-0.16	-0.12	-0.10	-0.09	-0.08	-0.05
	-2.99	-3.49	-3.72	-3.21	-3.15	-2.40	-2.08	-2.09	-2.14	-2.53
$\hat{p}_{JPY}$	-0.08	-0.07	-0.03	-0.03	-0.01	-0.02	-0.02	-0.02	-0.02	-0.04
	-2.13	-2.10	-1.08	-0.91	-0.33	-0.51	-0.68	-0.66	-0.65	-2.54
$\hat{p}_{KRW}$	0.05	0.05	0.02	-0.01	0.02	0.00	0.02	0.02	0.01	0.00
	1.14	1.39	0.65	-0.28	0.40	-0.05	0.56	0.60	0.24	0.16
$\hat{p}_{ZAR}$	0.08	0.04	0.04	0.04	0.05	0.05	0.04	0.05	0.03	0.00
	2.47	1.78	1.65	1.42	2.21	1.87	1.49	2.05	1.38	0.26
$\hat{g}$	0.29	0.00	0.02	-0.03	-0.06	-0.02	0.10	0.11	0.11	0.10
	2.06	0.01	0.17	-0.35	-0.58	-0.13	0.77	1.00	1.22	1.33
Adj. R^2	0.83	0.88	0.88	0.87	0.85	0.83	0.84	0.87	0.90	0.97

Table 17

Multiple risk-adjusted performance of portfolios classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. Panel A presents parameter estimates of an asset-pricing model adjusting for multiple risks i.e. market risk, infrequent trading, financial distress risk, business cycle risk, the January effect and exchange risks

$$r_{it} - r_{ft} = \alpha_i + \sum_{n=-1}^{0} \beta_{in}(r_{mt+n} - r_{ft+n}) + \sigma_i SMB_t + \theta_i HML_t + \pi_i PREM_t + \mu_i D_t + \sum_{k=2,4,5,7} \psi_{ik} XF_{kt} + \varsigma_i CXF_{it} + \varepsilon_{it},$$

with $XF_{kt} = s_{kt} + r_{ft}^{k} - r_{ft}$,

with $CXF_{it} = \sum_{k=8}^{38} \omega_{it}^{k} XF_{kt}$ and $\omega_{it}^{k} = \frac{n_{it}^{k}}{\sum_{k=8}^{38} n_{it}^{k}}$

where r_{it} is the return of portfolio *i* in month *t*, r_{ft} is the one-month U.S. T-Bill rate for month *t* (downloaded from Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/); r_{mt} the return of the TRD World Market Index (as proxy for the market portfolio); SMB_t and HML_t are calculated according to Fama and French (1993), except for equally weighting, monthly updating and global breakpoints.[1] We follow Chan et al. (1985) to measure the changing risk premium by measuring the behavior of bonds of different perceived riskiness. $PREM_t$ is the difference the return on a portfolio of "junk" bonds and the return on a portfolio of long-term government bonds.[2] The variable $PREM_t$ is intended to capture changes in the expected premium on risky assets.[3] D_t is the January dummy variable. XF_{kt} the k^{th} exchange factor for month *t* where *k* denotes the k^{th} currency (see Table 13, for the k^{th} currency); s_{kt} is the percentage change of the k^{th} exchange rate (against the USD)[4] for month *t*, r_{ft}^{k} is the proxy for the k^{th} one-month risk-free interest rate (see Table 13, for the proxy of the one-month risk-free interest rate associated with the k^{th} currency); CXF_{it} is the compounded exchange factor tailored for the i^{th} size decile which is calculated as the weighted average of the other exchange factors weighted by the number of stocks denominated in the k^{th} currency in decile *i* at time *t*, or n_{it}^{k}. If XF_{kt} is missing, due to an unavailable r_{ft}^{k}, we set XF_{kt} equal to s_{kt} to avoid an undesired reduction of the regression period.[5] Numbers in small case are White's heteroskedasticity-consistent *t*-statistics.

	S	2	3	4	5	6	7	8	9	B
$\hat{\alpha}$ (%)	1.30	-0.30	-0.38	-0.26	-0.10	0.00	0.07	0.07	0.08	0.05
	9.36	-2.66	-3.44	-2.31	-0.84	0.03	0.56	0.61	0.86	0.90
$\hat{\beta}_{t-1}$	0.01	0.03	0.05	0.05	0.07	0.07	0.06	0.07	0.04	0.02
	0.24	0.91	1.84	1.46	1.97	1.90	1.74	2.17	1.33	1.72

[1] The Fama-French (1993) methodology and results are well known. It is therefore unnecessary to provide a lengthy review. We simply refer to the Fama and French (1993) paper that provides the corresponding methodology.

[2] The portfolio of "junk" bonds is instrumented by the BofA Merrill Lynch US High Yield 100 Index (H100) and the portfolio of long-term government bonds by the Bofa Merrill Lynch 10+ Year US Treasury Index (G9O2). Although this is an international study, we preferred US indices because government bonds of low-rated countries are not a good proxy for the long-term riskless asset. We did not have access to sufficient historical data from other high-quality providers. Further details on the indices can be found on http://www.mlindex.ml.com

[3] Chan et al. (1985) hypotheses that the risk premium may change as a result of changing business conditions i.e. the business cycle

[4] To maximize the availability, exchange rates are first downloaded from TRD as WM/Reuters rates against GBP and, then, converted against USD using the WM/Reuters USD/GBP exchange rate.

[5] Setting XF_{kt} equal to s_{kt} assumes that $r_{ft}^{k} = r_{ft}$, which is generally not the case. The alternative is setting XF_{kt} equal to zero, which assumes that, under CIP, the forward rate perfectly predicts the future spot rate, which is empirically massively rejected. We applied both and the results are comparable. However, we do have a preference for setting XF_{kt} equal to s_{kt} as r_{ft} is the leading interest rate of other currencies and, therefore, most of the variability of XF_{kt} comes from the variability in s_{kt}

$\hat{\beta}$	0.94	0.94	0.91	0.93	0.89	0.87	0.88	0.90	0.95	1.00
	20.53	24.42	24.17	19.59	17.46	15.57	16.39	19.06	22.87	56.86
$\hat{\sigma}$	1.55	1.37	1.15	0.98	0.75	0.51	0.33	0.21	0.11	0.02
	14.05	22.78	18.53	16.39	12.19	7.81	5.20	3.51	2.09	0.63
$\hat{\theta}$	0.12	0.13	0.10	0.08	0.03	0.00	-0.03	-0.05	-0.04	-0.02
	1.89	3.73	2.52	2.29	0.81	-0.05	-0.81	-1.38	-0.97	-0.85
$\hat{\pi}$	0.02	0.06	0.05	0.07	0.07	0.10	0.09	0.08	0.07	0.01
	0.46	1.72	1.65	2.21	2.44	2.82	2.93	3.03	2.36	0.47
$\hat{\mu}$	1.73	0.43	0.32	0.00	-0.29	0.09	0.15	0.19	-0.01	-0.25
	3.13	1.28	0.94	0.00	-0.72	0.21	0.36	0.52	-0.02	-1.62
$\hat{\psi}_{CAD}$	0.15	0.15	0.16	0.16	0.17	0.16	0.15	0.14	0.11	0.04
	1.92	2.23	2.62	2.41	2.65	2.34	2.24	2.23	2.11	1.45
$\hat{\psi}_{GBP}$	-0.21	-0.16	-0.15	-0.12	-0.14	-0.11	-0.09	-0.08	-0.07	-0.05
	-3.64	-3.62	-3.41	-2.74	-2.84	-2.18	-1.88	-1.98	-1.98	-2.39
$\hat{\psi}_{JPY}$	-0.09	-0.06	-0.03	-0.02	0.00	-0.01	-0.01	-0.01	-0.01	-0.04
	-2.18	-1.81	-0.88	-0.60	0.03	-0.16	-0.32	-0.29	-0.31	-2.39
$\hat{\psi}_{ZAR}$	0.07	0.04	0.04	0.04	0.06	0.05	0.04	0.04	0.03	0.01
	2.16	1.72	1.92	1.66	2.38	1.83	1.54	2.02	1.44	0.59
$\hat{\varsigma}$	0.14	0.06	0.05	0.08	0.12	0.13	0.14	0.12	0.09	0.05
	1.85	0.99	0.88	1.29	1.69	1.71	1.98	2.02	1.75	1.68
Adj. R^2	0.83	0.88	0.88	0.87	0.85	0.83	0.84	0.88	0.91	0.97

Table 18

Descriptive statistics on dividend yield and size portfolios

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their dividend yield (DY) and their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. The dividend yield is downloaded from Thomson Reuters Datastream and expresses the dividend per share as a percentage of the share price. The underlying dividend is the annualized dividend rate. It is intended to represent the anticipated payment over the following 12 months and for that reason may be calculated on a rolling 12-month basis, or as the "indicated" annual amount, or it may be a forecast. Special or once-off dividends are generally excluded. Dividends per share are displayed gross, inclusive of local tax credits where applicable, except for France, Belgium, Ireland and the UK, where dividends per share are displayed net. All averages are time-series averages of monthly equally-weighted returns, dividend yields and distributions.

DY Portfolios	Monthly Return	6-Month Past Return	Size Portfolios	Positive DY		Zero DY	
Zero	1.35%	1.94%		Avg	Std	Avg distibution	Std distribution
Lowest (+)	0.77%	3.33%	Smallest	4.48	1.21	17.59%	2.34%
2	0.95%	2.11%	2	4.16	2.26	15.19%	2.26%
3	1.11%	1.70%	3	4.00	1.94	13.50%	1.77%
4	1.22%	1.59%	4	3.74	1.59	11.80%	0.98%
5	1.20%	1.53%	5	3.34	1.02	10.44%	0.73%
6	1.27%	1.39%	6	2.98	0.78	8.96%	1.09%
7	1.45%	1.19%	7	2.90	0.84	7.83%	1.43%
8	1.63%	0.99%	8	2.77	0.84	6.67%	1.72%
9	1.74%	0.71%	9	2.75	0.94	5.05%	1.77%
Highest	1.85%	0.06%	Biggest	2.90	1.10	2.96%	1.29%

Table 19
The marginal ability of (zero-)dividend yield to explain the cross-section of portfolio returns classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. The table presents the statistics of the parameter estimates of the following Fama-Macbeth (1973) regressions, one for each month *t*,

$$\alpha_i + \varepsilon_{it} = a_t + d_t DY_{it} + z_t ZDY_{it} + e_{it},$$

where $\alpha_i + \varepsilon_{it}$ is the risk-adjusted return of portfolio *i* in month *t* according to the full model in Table 17 (Panel A) or the conditional model in Table 22 (Panel B), DY_{it} is the equally-weighted (positive) dividend yield of portfolio *i* in month *t*, and ZDY_{it} is the proportion of zero-dividend yield stocks of portfolio *i* in month *t*.

Panel A: FM parameters of the full model			
	a_t	d_t	z_t
Mean	-1.00	0.45	-0.02
T-Statistic	-5.14	4.98	-1.02
Median	-0.63	0.15	-0.03
Maximum	12.89	7.06	1.97
Minimum	-11.96	-6.30	-1.28
Std. Dev.	3.63	1.69	0.31
Skewness	-0.09	0.09	1.22
Kurtosis	4.43	4.88	11.06
Jarque-Bera	30.68	52.50	1040.35
Probability	0.00	0.00	0.00
Sum	-350.40	157.42	-5.90
Sum Sq. Dev.	4627.69	997.98	33.23
Observations	352	352	352

Panel B: FM parameters of the conditional model			
	a_t	d_t	z_t
Mean	-0.89	0.41	-0.01
T-Statistic	-4.58	4.47	-0.79
Median	-0.46	0.16	-0.03
Maximum	12.28	6.75	1.93
Minimum	-11.52	-7.05	-1.21
Std. Dev.	3.65	1.74	0.31
Skewness	-0.06	-0.03	1.16
Kurtosis	4.18	4.88	11.12
Jarque-Bera	20.52	51.65	1045.41
Probability	0.00	0.00	0.00
Sum	-313.95	145.92	-4.63
Sum Sq. Dev.	4681.15	1064.41	34.17
Observations	352	352	352

Table 20
The marginal ability of (zero-)dividend yield to explain the variation over time of portfolio returns classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. The table presents the parameter estimates of the following time-series regressions, one for each portfolio *i*,

$$\alpha_i + \varepsilon_{it} = a_i + d_i DY_{it} + z_i ZDY_{it} + e_{it},$$

where $\alpha_i + \varepsilon_{it}$ is the risk-adjusted return of portfolio *i* in month *t* according to the Full model in Table 17, DY_{it} is the equally-weighted (positive) dividend yield of portfolio *i* in month *t*, and ZDY_{it} is the proportion of zero-dividend yield stocks of portfolio *i* in month *t*.

	S	2	3	4	5	6	7	8	9	B
$\hat{a}$ (%)	5.60	1.06	0.59	2.22	0.14	-3.47	-1.14	-1.01	-1.08	-0.41
	5.97	1.59	0.78	1.70	0.10	-2.81	-1.32	-1.83	-2.46	-1.74
$\hat{d}$	0.26	0.14	0.02	0.12	0.13	0.50	0.20	0.19	0.20	0.06
	2.46	3.32	0.31	1.96	1.44	3.68	1.92	2.31	2.68	1.16
$\hat{z}$	-0.31	-0.13	-0.08	-0.25	-0.06	0.22	0.08	0.08	0.12	0.10
	-5.37	-2.75	-1.25	-2.14	-0.48	2.12	0.96	1.45	2.21	2.02
Adj. R^2	0.09	0.04	0.00	0.02	0.00	0.02	0.00	0.01	0.02	0.01

Table 21
The marginal ability of (zero-)dividend yield and their cross-terms to explain the variation over time of portfolio returns classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. The table presents the parameter estimates of the following time-series regressions, one for each portfolio *i*,

$$\alpha_i + \varepsilon_{it} = a_i + d_i DY_{it} + z_i ZDY_{it} + \sum_{n=1}^{11} d_i^n (X_{it}^n * DY_{it}) + \sum_{n=1}^{11} z_i^n (X_{it}^n * ZDY_{it}) + e_{it},$$

where $\alpha_i + \varepsilon_{it}$ is the risk-adjusted return of portfolio *i* in month *t* according to the full model in Table 17, DY_{it} is the equally-weighted (positive) dividend yield of portfolio *i* in month *t*, and ZDY_{it} is the proportion of zero-dividend yield stocks of portfolio *i* in month *t*., and X_{it}^n the n^{th} risk factor of the full model in Table 17 of portfolio *i* in month *t*. For reasons of simplicity we only report the significant parameter estimates, the others are available upon request.

	S	2	3	4	5	6	7	8	9	B
$\hat{a}$ (%)	5.45	0.94	0.83	1.98	0.72	-3.44	-1.20	-1.20	-1.02	-0.38
	5.45	1.40	1.04	1.56	0.46	-2.63	-1.33	-1.91	-2.26	-1.71
$\hat{d}$	0.37	0.32	0.08	0.20	0.09	0.46	0.23	0.22	0.17	0.02
	3.20	2.88	1.43	2.17	0.93	3.18	2.07	2.16	2.17	0.32
$\hat{z}$	-0.32	-0.16	-0.11	-0.25	-0.11	0.23	0.08	0.10	0.12	0.13
	-5.60	-3.15	-1.72	-2.17	-0.73	2.01	0.86	1.41	2.03	2.87
$(r_m - r_f) * DY$	0.07	0.03	0.02	0.02	0.08	0.09	0.06	0.06	0.06	0.03
	2.09	1.45	0.94	0.77	2.50	2.62	2.23	2.28	2.95	3.18
$(r_m - r_f) * ZDY$	-0.02	-0.01	-0.01	-0.01	-0.03	-0.03	-0.02	-0.02	-0.03	-0.03
	-2.49	-1.29	-0.95	-0.87	-2.28	-2.33	-2.23	-2.25	-2.67	-2.85
$XF_{GBP} * DY$	-0.12	0.05	0.04	0.06	0.01	0.01	0.03	0.01	0.02	0.02
	-2.95	1.20	1.26	2.07	0.29	0.17	1.01	0.39	1.24	1.68
$XF_{GBP} * ZDY$	0.03	-0.01	-0.01	-0.02	0.00	0.00	-0.01	0.00	-0.02	-0.02
	3.04	-1.01	-1.13	-1.67	-0.17	-0.07	-0.77	-0.32	-1.33	-1.76
$CFX * DY$	0.20	0.00	-0.03	-0.03	0.02	0.05	0.01	-0.03	-0.03	-0.02
	3.29	-0.01	-1.08	-0.82	0.39	0.77	0.26	-0.60	-1.13	-1.45
$CFX * ZDY$	-0.06	0.00	0.01	0.01	-0.01	-0.02	-0.01	0.02	0.03	0.04
	-3.51	-0.04	0.73	0.84	-0.40	-0.61	-0.23	0.64	1.34	1.82
$SMB * DY$	0.20	0.05	-0.07	-0.11	-0.11	-0.09	-0.08	-0.04	-0.03	0.02
	4.19	1.48	-1.89	-2.30	-1.63	-1.46	-1.66	-0.85	-0.82	0.88
$SMB * ZDY$	-0.06	-0.01	0.02	0.03	0.03	0.03	0.03	0.01	0.01	-0.01
	-4.46	-1.38	1.42	1.92	1.43	1.33	1.45	0.77	0.77	-0.87
Adj. R^2	0.16	0.04	-0.01	0.02	-0.01	0.01	-0.03	-0.03	0.01	0.08

Table 22
Multiple risk-adjusted performance with time-varying risk loadings linearly related to (zero-)dividend yield of portfolios classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. Panel A presents parameter estimates of an asset-pricing model adjusting for multiple risks i.e. market risk, infrequent trading, financial distress risk, business cycle risk, the January effect and exchange risks and allowing for the risk-loadings of the market risk factor, the 4th exchange risk factor i.e. GBP, the compounded risk factors and the Fama-French size risk factor to vary over time linearly related to (zero-)dividend yield.

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \beta_i^{dy}(r_{mt} - r_{ft}) * dy_{it} + \beta_i^{zdy}(r_{mt} - r_{ft}) * zdy_{it} + \sigma_i SMB_t + \sigma_i^{dy} SMB_t * dy_{it} + \sigma_i^{zdy} SMB_t * zdy_{it} + \theta_i HML_t + \pi_i PREM_t + \mu_i D_t + \sum_{k=2,4,5,7} \psi_{ik} XF_{kt} + \psi_{i4}^{dy} XF_{4t} * dy_{it} + \psi_{i4}^{zdy} XF_{4t} * zdy_{it} + \varsigma_i CXF_{it} + \varsigma_i^{dy} CXF_{it} * dy_{it} + \varsigma_i^{zdy} CXF_{it} * zdy_{it} + \varepsilon_{it},$$

$$\text{with } XF_{kt} = s_{kt} + r_{ft}^k - r_{ft},$$

$$\text{with } CXF_{it} = \sum_{k=8}^{38} \omega_{it}^k XF_{kt} \text{ and } \omega_{it}^k = \frac{n_{it}^k}{\sum_{k=8}^{38} n_{it}^k}$$

$$\text{with } dy_{it} = DY_{it} - \overline{DY_\iota} \text{ and } zdy_{it} = ZDY_{it} - \overline{ZDY_\iota}$$

where r_{it} is the return of portfolio *i* in month *t*, r_{ft} is the one-month U.S. T-Bill rate for month *t* (downloaded from Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/); r_{mt} the return of the TRD World Market Index (as proxy for the market portfolio); SMB_t and HML_t are calculated according to Fama and French (1993), except for equally weighting, monthly updating and global breakpoints.[1] We follow Chan et al. (1985) to measure the changing risk premium by measuring the behavior of bonds of different perceived riskiness. $PREM_t$ is the difference the return on a portfolio of "junk" bonds and the return on a portfolio of long-term government bonds.[2] The variable $PREM_t$ is intended to capture changes in the expected premium on risky assets.[3] D_t is the January dummy variable. XF_{kt} the k^{th} exchange factor for month *t* where *k* denotes the k^{th} currency (see Table 13, for the k^{th} currency); s_{kt} is the percentage change of the k^{th} exchange rate (against the USD)[4] for month *t*, r_{ft}^k is the proxy for the k^{th} one-month risk-free interest rate (see Table 13, for the proxy of the one-month risk-free interest rate associated with the k^{th} currency); CXF_{it} is the compounded exchange factor tailored for the i^{th} size decile which is calculated as the weighted average of the other exchange factors weighted by the number of stocks denominated in the k^{th} currency in decile *i* at time *t*, or n_{it}^k. If XF_{kt} is missing, due to an unavailable r_{ft}^k, we set XF_{kt} equal to s_{kt} to avoid an undesired reduction of the regression period.[5] DY_{it} is the equally-weighted (positive) dividend yield of portfolio *i* in month *t*, and ZDY_{it} is the proportion of

[1] The Fama-French (1993) methodology and results are well known. It is therefore unnecessary to provide a lengthy review. We simply refer to the Fama and French (1993) paper that provides the corresponding methodology.

[2] The portfolio of "junk" bonds is instrumented by the BofA Merrill Lynch US High Yield 100 Index (H100) and the portfolio of long-term government bonds by the Bofa Merrill Lynch 10+ Year US Treasury Index (G9O2). Although this is an international study, we preferred US indices because government bonds of low-rated countries are not a good proxy for the long-term riskless asset. We did not have access to sufficient historical data from other high-quality providers. Further details on the indices can be found on http://www.mlindex.ml.com

[3] Chan et al. (1985) hypotheses that the risk premium may change as a result of changing business conditions i.e. the business cycle

[4] To maximize the availability, exchange rates are first downloaded from TRD as WM/Reuters rates against GBP and, then, converted against USD using the WM/Reuters USD/GBP exchange rate.

[5] Setting XF_{kt} equal to s_{kt} assumes that $r_{ft}^k = r_{ft}$, which is generally not the case. The alternative is setting XF_{kt} equal to zero, which assumes that, under CIP, the forward rate perfectly predicts the future spot rate, which is empirically massively rejected. We applied both and the results are comparable. However, we do have a preference for setting XF_{kt} equal to s_{kt} as r_{ft} is the leading interest rate of other currencies and, therefore, most of the variability of XF_{kt} comes from the variability in s_{kt}

zero-dividend yield stocks of portfolio *i* in month *t*. Numbers in small case are White's heteroskedasticity-consistent *t*-statistics.

	S	2	3	4	5	6	7	8	9	B
$\hat{\alpha}$ (%)	1.39	-0.32	-0.41	-0.21	-0.08	0.04	0.10	0.09	0.07	0.05
	11.04	-3.12	-4.06	-1.99	-0.73	0.29	0.78	0.81	0.77	1.01
$\hat{\beta}$	0.89	0.95	0.93	0.94	0.91	0.90	0.89	0.92	0.95	1.00
	27.43	32.63	32.76	32.17	26.89	22.75	24.17	30.86	34.82	57.61
$\hat{\beta}^{dy}$	0.09	0.03	0.01	0.06	0.08	0.10	0.03	0.03	0.04	0.01
	2.66	3.51	0.50	4.21	3.12	2.71	0.90	1.06	1.68	0.98
$\hat{\beta}^{zdy}$	-0.01	0.02	0.03	0.03	0.02	0.00	-0.04	-0.01	-0.02	-0.01
	-0.43	1.74	1.90	1.26	0.52	0.18	-1.47	-0.91	-1.56	-0.42
$\hat{\sigma}$	1.41	1.32	1.10	0.96	0.75	0.46	0.30	0.19	0.09	0.00
	19.95	25.68	21.31	17.41	12.46	7.34	4.94	3.38	1.83	0.14
$\hat{\sigma}^{dy}$	0.08	-0.04	-0.04	-0.05	-0.04	0.08	-0.03	0.00	0.05	-0.01
	1.72	-2.01	-1.43	-1.38	-0.69	0.85	-0.43	-0.02	0.90	-0.24
$\hat{\sigma}^{zdy}$	-0.17	-0.09	-0.10	-0.03	0.03	0.17	0.04	0.03	0.05	0.02
	-5.30	-4.10	-3.88	-0.66	0.42	2.59	1.07	0.97	1.93	0.77
$\hat{\theta}$	0.15	0.15	0.12	0.07	0.01	-0.01	-0.04	-0.06	-0.03	-0.02
	3.03	4.77	3.65	2.06	0.28	-0.37	-0.93	-1.73	-0.93	-0.97
$\hat{\pi}$	0.05	0.07	0.08	0.10	0.08	0.10	0.11	0.09	0.08	0.01
	1.28	2.12	2.62	2.74	2.68	3.02	3.53	2.94	2.74	0.64
$\hat{\mu}$	1.63	0.28	0.22	0.04	-0.10	0.15	0.10	0.26	-0.01	-0.21
	3.52	0.87	0.65	0.10	-0.24	0.35	0.24	0.69	-0.03	-1.34
$\hat{\psi}_{CAD}$	0.17	0.14	0.16	0.14	0.17	0.15	0.16	0.12	0.10	0.03
	2.26	2.21	2.56	2.14	2.72	2.37	2.20	1.97	1.86	0.96
$\hat{\psi}_{GBP}$	-0.16	-0.14	-0.14	-0.10	-0.15	-0.09	-0.08	-0.09	-0.09	-0.06
	-3.18	-3.65	-3.48	-2.47	-3.11	-1.75	-1.60	-2.00	-2.26	-3.08
$\hat{\psi}_{GBP}^{dy}$	-0.12	0.02	0.01	0.05	0.00	-0.01	0.00	0.03	0.02	0.03
	-3.84	0.57	0.35	2.05	0.02	-0.17	0.06	0.61	0.41	1.63
$\hat{\psi}_{GBP}^{zdy}$	0.03	0.00	0.02	-0.09	0.03	-0.06	-0.03	-0.01	-0.03	-0.02
	1.36	-0.19	0.99	-1.73	0.44	-1.49	-0.76	-0.37	-1.35	-1.02
$\hat{\psi}_{JPY}$	-0.09	-0.07	-0.04	-0.01	0.02	-0.01	-0.01	0.00	-0.01	-0.04
	-2.41	-2.16	-1.37	-0.30	0.55	-0.17	-0.30	-0.05	-0.41	-2.36
$\hat{\psi}_{ZAR}$	0.06	0.04	0.04	0.03	0.05	0.05	0.04	0.04	0.03	0.00
	2.19	1.94	1.82	1.22	2.13	2.01	1.52	1.58	1.32	0.26
$\hat{\varsigma}$	0.07	0.10	0.13	0.17	0.12	0.09	0.17	0.22	0.20	0.11
	0.96	1.58	1.94	2.47	1.31	0.86	1.59	2.57	2.65	3.04
$\hat{\varsigma}^{dy}$	0.18	-0.02	-0.01	-0.08	-0.04	0.07	0.10	0.04	0.02	-0.03
	3.20	-0.55	-0.33	-2.66	-0.58	0.86	1.42	0.57	0.47	-0.97
$\hat{\varsigma}^{zdy}$	-0.06	-0.05	-0.11	-0.10	-0.13	0.12	0.13	0.11	0.12	0.09
	-2.23	-1.96	-2.93	-1.64	-1.53	1.80	1.96	2.25	3.11	2.54
Adj. R^2	0.86	0.90	0.89	0.88	0.86	0.84	0.84	0.88	0.91	0.97

Table 23

Micro-size risk adjusted performance of portfolios classified by size

At the beginning of each month from January 1980 to May 2009, stocks are sorted in ascending order based on their size, the dollar market capitalization. Based on each sort, stocks are grouped into equally-weighted decile portfolios based on global breakpoints and held for one month. S denotes the smallest decile portfolio, B denotes the biggest decile portfolio. Panel A presents parameter estimates of the 'custom-made' asset pricing model

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + s_i SMB_t^* + s_i^m mSMB_t^* + \varepsilon_{it},$$

where r_{it} is the return of portfolio i in month t, r_{ft} is the one-month T-bill rate for month t, and r_{mt} the return of the TRD World Market Index (proxy for the market portfolio). Numbers in small case are White's heteroskedasticity-consistent t-statistics. SMB_t^* and $m(icro)SMB_t^*$ are the returns for month t of, respectively, the zero-investment portfolio long in the 50% smallest stocks and short in the 50% largest stocks, and long the 10% smallest stocks and short the 40% larger-than-smallest stocks. SMB_t^* and $mSMB_t^*$ are not calculated from the Fama and French (1993) S/L, S/M, S/H, B/L, B/M, B/H portfolios but directly from (one-dimensionally sorted) equally-weighted and monthly-updated size portfolios based on global breakpoints.

	S	2	3	4	5	6	7	8	9	B
$\hat{\alpha}$ (%)	0.09	-0.19	0.00	0.27	0.28	0.19	0.17	0.06	0.04	-0.01
	0.67	-1.63	0.04	1.88	1.60	1.06	1.00	0.36	0.30	-0.15
$\hat{\beta}$	1.01	1.01	1.00	1.02	1.00	1.00	0.99	1.01	1.03	1.01
	48.75	49.50	51.83	44.93	40.05	37.03	37.71	42.07	50.63	77.45
$\hat{s}$	1.31	1.57	1.44	1.28	0.96	0.67	0.44	0.27	0.16	0.03
	22.59	27.42	24.65	20.03	14.40	8.82	5.95	3.97	2.65	0.80
$\hat{s}^m$	0.71	-0.12	-0.31	-0.40	-0.32	-0.20	-0.14	-0.07	-0.03	0.00
	9.21	-1.86	-4.10	-4.89	-3.24	-1.93	-1.46	-0.77	-0.44	-0.01
Adj. R^2	0.93	0.92	0.91	0.89	0.86	0.83	0.83	0.87	0.90	0.97

Table 24

Spearman rank correlation analysis of the ad-hoc (micro-)size risk factors

From January 1980 to May 2009, SMB_t and HML_t are calculated according to Fama and French (1993), except for equally weighting, monthly updating and global breakpoints.[1] SMB_t^*, HML_t^* and $mSMB_t^*$ are not calculated from the S/L, S/M, S/H, B/L, B/M, B/H portfolios but directly from (one-dimensionally sorted) size and book-to-market portfolios. Therefore, firms with missing book value do play a role in SMB_t^* and $mSMB_t^*$, but not in SMB_t. $m(icro)SMB_t^*$ is the return for month *t* of the zero-investment portfolio long the 10% smallest stocks and short the 40% larger-than-smallest stocks. r_{mt} is the return of the TRD World Market Index (proxy for the market portfolio). $XF_{kt} = s_{kt} + r_{ft}^k - r_{ft}$ with XF_{kt} the k^{th} exchange factor for month *t* where *k* denotes the k^{th} currency i.e. Australian dollar (AUD), Canadian dollar (CAD), German mark (DEM), British pound (GBP), Japanese yen (JPY), Korean won (KRW) and South-African rand (ZAR); s_{kt} is the percentage change of the k^{th} exchange rate[2] for month *t*, r_{ft}^k is the proxy for the k^{th} one-month risk-free interest rate (see Table 13, for the proxy of the one-month risk-free interest rate associated with the k^{th} currency); and r_{ft} is the one-month T-bill rate for month *t*. DY_t is the return for month *t* of an ad-hoc "dividend yield risk factor" calculated as the zero-investment portfolio long in the 30% highest dividend yield stocks and short in the 30% lowest (but positive) dividend yield stocks. D_t is the January dummy variable. We follow Lui (2006) to calculate LIQ_t. At the beginning of each month, stocks are sorted in ascending order based on their illiquidity measure $ILL12$. Based on each sort, stocks are grouped into two equally-weighted portfolios. The high-illiquidity portfolio contains the 30% highest illiquidity stocks. The low-illiquidity portfolio contains the 30% lowest illiquidity stocks. The breakpoints are set globally. The two portfolios are held for six months after portfolio formation. We calculate the monthly average return across six strategies, each starting one month apart to handle the issue of overlapping observations. LIQ_t is then constructed as the monthly profits from buying one dollar of equally weighted high-illiquidity and selling one dollar of equally weighted low-illiquidity. We follow Lee (2010) to calculate the illiquidity measure $ILL12$. The monthly proxy for illiquidity, $ILL1$, is calculated as the ratio of the number of zero-return days to the number of trading days in a given month.[3] $ILL12$ is the average $ILL1$ over the prior 12 months. Before May 1988 the dispersion of the illiquidity measure $ILL12$ was quite small.[4] Therefore, we calculate LIQ_t from May 1988 till May 2009. We follow Rouwenhorst (1999) to calculate MOM_t. At the beginning of each month, stocks are sorted in ascending order based on their prior six-month return. Based on each sort, stocks are grouped into two equally-weighted portfolios. The *winners* portfolio contains the 30% highest past performers. The *losers* portfolio contains the 30% lowest past performers. The breakpoints are set globally. The two portfolios are held for six months after portfolio formation. We calculate the monthly average return across six strategies, each starting one month apart to handle the issue of overlapping observations. To attenuate the effect of bid-ask bounce the portfolios are formed one month after the end of the ranking

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[1] The Fama-French (1993) methodology and results are well known. It is therefore unnecessary to provide a lengthy review. We simply refer to the Fama and French (1993) paper that provides the corresponding methodology.

[2] To maximize the availability, exchange rates are first downloaded from TRD as WM/Reuters rates against GBP and, then, converted against USD using the WM/Reuters USD/GBP exchange rate.

[3] It is important to exclude non-trading days from the sample because TRD fills a non-trading day with the total return index of the prior trading day, a process that inflates zero-return proportions. Lee (2010) identifies a non-trading day if more than 90% of stocks in a given exchange have zero returns on that day. Although it is possible to download the monthly number of zero returns directly from TRD, following Lee (2010) in correcting for non-trading days would still require downloading daily data, which can be quite cumbersome for large datasets. We, therefore, identify the monthly non-trading days as the number of zero returns of the local index of a given exchange. The list of local indices is in Appendix A. We tested the reliability of this approach on a subsample of countries by comparing the zero daily local index returns: (i) with other third-party country indices (we found the local indices more reliable than third-party indices for this purpose); (ii) with internet resources on stock exchange holidays such as the exchange's website; (iii) with the daily returns of a subsample of large companies on the exchange; (iv) with, if available, the VACS datatype in TRD which returns the stock exchange non-trading days. In case of multiple stock exchanges in one country we found no example of non-synchronic non-trading days, such that the local index suits for all exchanges in a country.

[4] Before May 1988 stocks with an $ILL12$ measure of zero occupied more than one decile liquidity portfolio.

period. MOM_t is then constructed as the monthly profits from buying one dollar of equally weighted *winners* and selling one dollar of equally weighted *losers*.

We follow Chan et al. (1985) to measure the changing risk premium by measuring the behavior of bonds of different perceived riskiness. $PREM_t$ is the difference the return on a portfolio of "junk" bonds and the return on a portfolio of long-term government bonds.[5] The variable $PREM_t$ is intended to capture changes in the expected premium on risky assets.[6] Numbers in small case are the *t*-statistics.

Panel A: Spearman rank correlations of SMB_t^* conditional on $r_{mt} - r_{ft}$, SMB_t, HML_t and $mSMB_t^*$

DY_t	D_t	MOM_t	LIQ_t	$PREM_t$	XF_{AUD}	XF_{CAD}	XF_{DEM}	XF_{GBP}	XF_{JPY}	XF_{KRW}	XF_{ZAR}
0.17	-0.03	0.17	0.07	-0.06	-0.02	0.07	-0.04	-0.18	-0.07	0.03	-0.06
2.60	-0.44	2.64	1.08	-0.93	-0.38	1.01	-0.56	-2.77	-1.11	0.49	-0.95

Panel B: Spearman rank correlations of $mSMB_t^*$ conditional on $r_{mt} - r_{ft}$, SMB_t, HML_t and SMB_t^*

DY_t	D_t	MOM_t	LIQ_t	$PREM_t$	XF_{AUD}	XF_{CAD}	XF_{DEM}	XF_{GBP}	XF_{JPY}	XF_{KRW}	XF_{ZAR}
0.13	0.21	-0.01	-0.02	0.07	-0.09	-0.10	-0.13	-0.04	-0.13	-0.09	-0.05
1.93	3.28	-0.19	-0.28	1.06	-1.40	-1.57	-1.96	-0.61	-2.07	-1.33	-0.80

[5] The portfolio of "junk" bonds is instrumented by the BofA Merrill Lynch US High Yield 100 Index (H100) and the portfolio of long-term government bonds by the Bofa Merrill Lynch 10+ Year US Treasury Index (G9O2). Although this is an international study, we preferred US indices because government bonds of low-rated countries are not a good proxy for the long-term riskless asset. We did not have access to sufficient historical data from other high-quality providers. Further details on the indices can be found on http://www.mlindex.ml.com

[6] Chan et al. (1985) hypothise that the risk premium may change as a result of changing business conditions i.e. the business cycle

Table 25
The associated stock index per stock exchange

Stock Exchange	Country	Stock Index
Alberta	Canada	S&P/TSX Composite Index
Alternext US	U.S.	S&P 500
Amsterdam (AEX)	Netherlands	AEX
Amsterdam Unlist	Netherlands	AEX
Athens	Greece	FTSE/ATHEX 20
Australian	Australia	ASX All Ordinairies
Berlin	Germany	Dax 30
Berne	Switzerland	Swiss Market
Bogota	Colombia	Colombia IGBC Index
Bombay	India	India BSE
Bordeaux	France	CAC 40
Brussels	Belgium	Brussels All Share
Brussels Terme	Belgium	Brussels All Share
Buenos Aires	Argentina	Argentina Merval
Bursa Malaysia	Malaysia	FTSE Bursa Malaysia
Catalist	Singapore	Straits Times
Copenhagen	Denmark	OMX Copenhagen
Dublin	Ireland	Ireland SE Overall
Dusseldorf	Germany	Dax 30
Euron. Amsterdam	Netherlands	AEX
Euron. Brussels	Belgium	Brussels All Share
Euronext Lisbon	Portugal	PSI 20
Euronext Paris	France	CAC 40
Frankfurt	Germany	Dax 30
Fukuoka	Japan	Topix
Geneva	Switzerland	Swiss Market
Hamburg	Germany	Dax 30
Hannover	Germany	Dax 30
Helsinki	Finland	OMX Helsinki
Hong Kong	Hong Kong	Hang Seng
Indonesia SE	Indonesia	Jakarta SE
Jasdaq	Japan	Topix
Johannesburg	South Africa	FTSE/JSE All Share
Korea	Korea	Korea SE Composite (KOSPI)
Kosdaq	Korea	Korea SE Composite (KOSPI)
Lille	France	CAC 40
Lima	Peru	Lima SE Selective (ISBL)
Lisbon	Portugal	PSI 20
London	U.K.	FTSE All Share
London Plus Mkt	U.K.	FTSE All Share
Luxembourg	Luxembourg	Luxembourg SE General
Lyon	France	CAC 40
Madrid	Spain	IBEX 35
Madrid-SIBE	Spain	IBEX 35
Malaysia 2nd Boa	Malaysia	FTSE Bursa Malaysia
Malaysia Mesdaq	Malaysia	FTSE Bursa Malaysia
Marseilles	France	CAC 40
Mexico City	Mexico	Mexico IPC (BOLSA)
Milan	Italy	Milan Comit
Montreal	Canada	S&P/TSX Composite Index
Munich	Germany	Dax 30
Nagoya	Japan	Topix
Nancy	France	CAC 40
Nantes	France	CAC 40
Nasdaq	U.S.	S&P 500
Nasdaq Smallcap	U.S.	S&P 500

National India	India	India BSE
New York	U.S.	S&P 500
New Zealand	New Zealand	NZX 50
NYSE Amex	U.S.	S&P 500
NYSE ARCA	U.S.	S&P 500
Osaka	Japan	Topix
Oslo	Norway	Oslo SE OBX
OTC Bull.Bd.Nasd	U.S.	S&P 500
Other OTC Nasdaq	U.S.	S&P 500
Pacific	U.S.	S&P 500
Paris-SBF	France	CAC 40
Philippine SE	Philippines	Philippine SE I (PSEi)
Santiago	Chili	Chile Selective (IPSA)
Sao Paulo	Brazil	Brazil Bovespa
Sapporo	Japan	Topix
Shanghai	China	Shanghai SE Composite
Shenzen	China	Shanghai SE Composite
Singapore	Singapore	Straits Times
Singapore OTC	Singapore	Straits Times
SIX Swiss	Switzerland	Swiss Market
Stockholm	Sweden	OMX Stockholm 30
Stuttgart	Germany	Dax 30
Swiss SE	Switzerland	Swiss Market
SWX Europe	Switzerland	Swiss Market
Taiwan	Taiwan	Taiwan SE Weighted
Taiwan OTC	Taiwan	Taiwan SE Weighted
Thailand	Thailand	Bangkok S.E.T. 50
Tokyo	Japan	Topix
Toronto	Canada	S&P/TSX Composite Index
TSX Venture	Canada	S&P/TSX Composite Index
Vienna	Austria	Austria Traded Index (ATX)

Figure 1
Average geographical distribution of the pooled sample and the sample of smallest stocks (in terms of number of firms)

This figure is the graphical representation of column 4 and the last-but-one column of Table 1. A smallest firm is defined as having its market capitalization in the first size decile of the pooled sample. The size breakpoints are updated monthly.

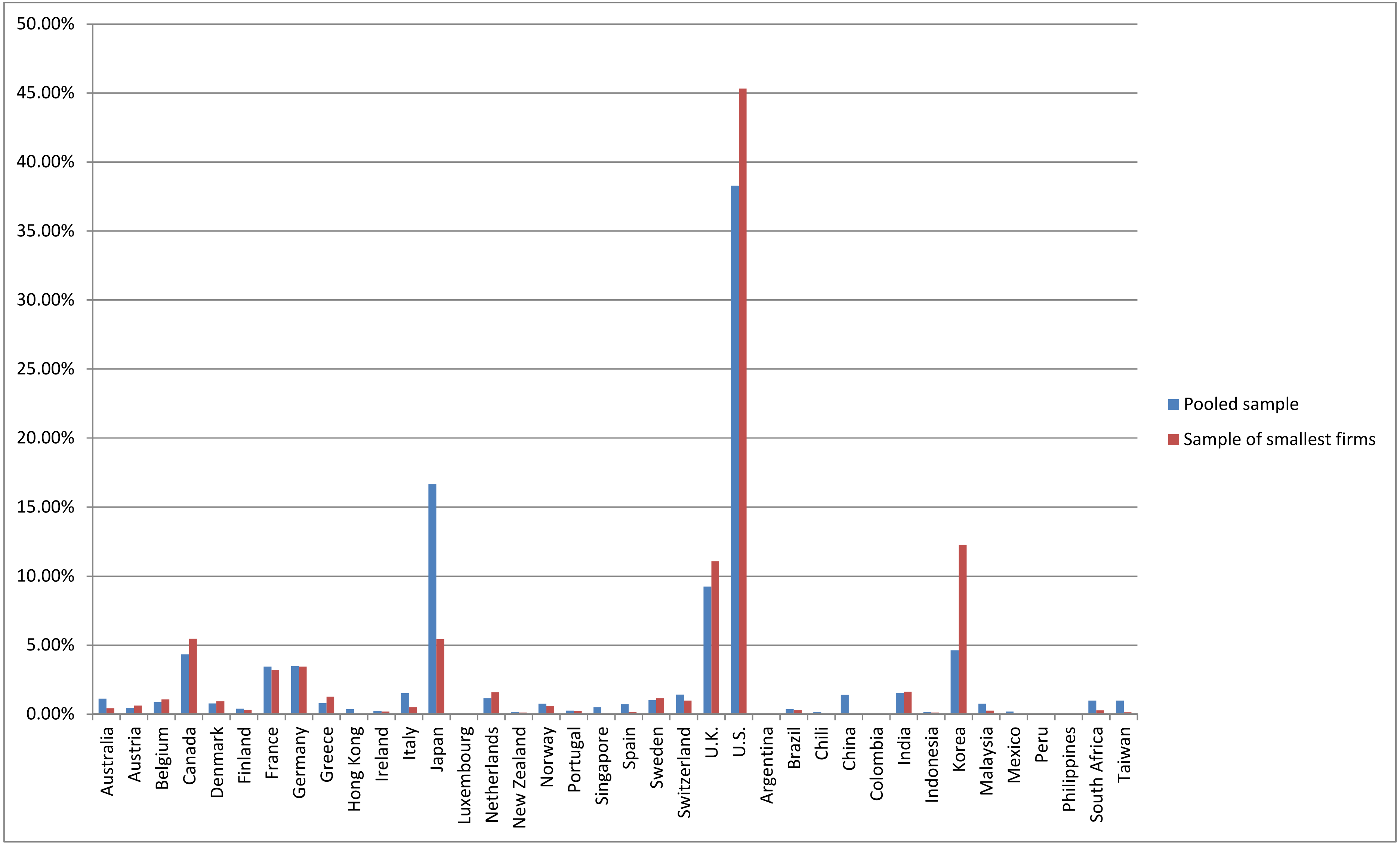

Figure 2
Sector distribution of the pooled sample and sample of smallest stocks, in terms of the average number of (smallest) ongoing firms

This figure is the graphical representation of column 4 and the last-but-one column of Table 2. A smallest firm is defined as having its market capitalization in the first size decile of the pooled sample. The size breakpoints are updated monthly.

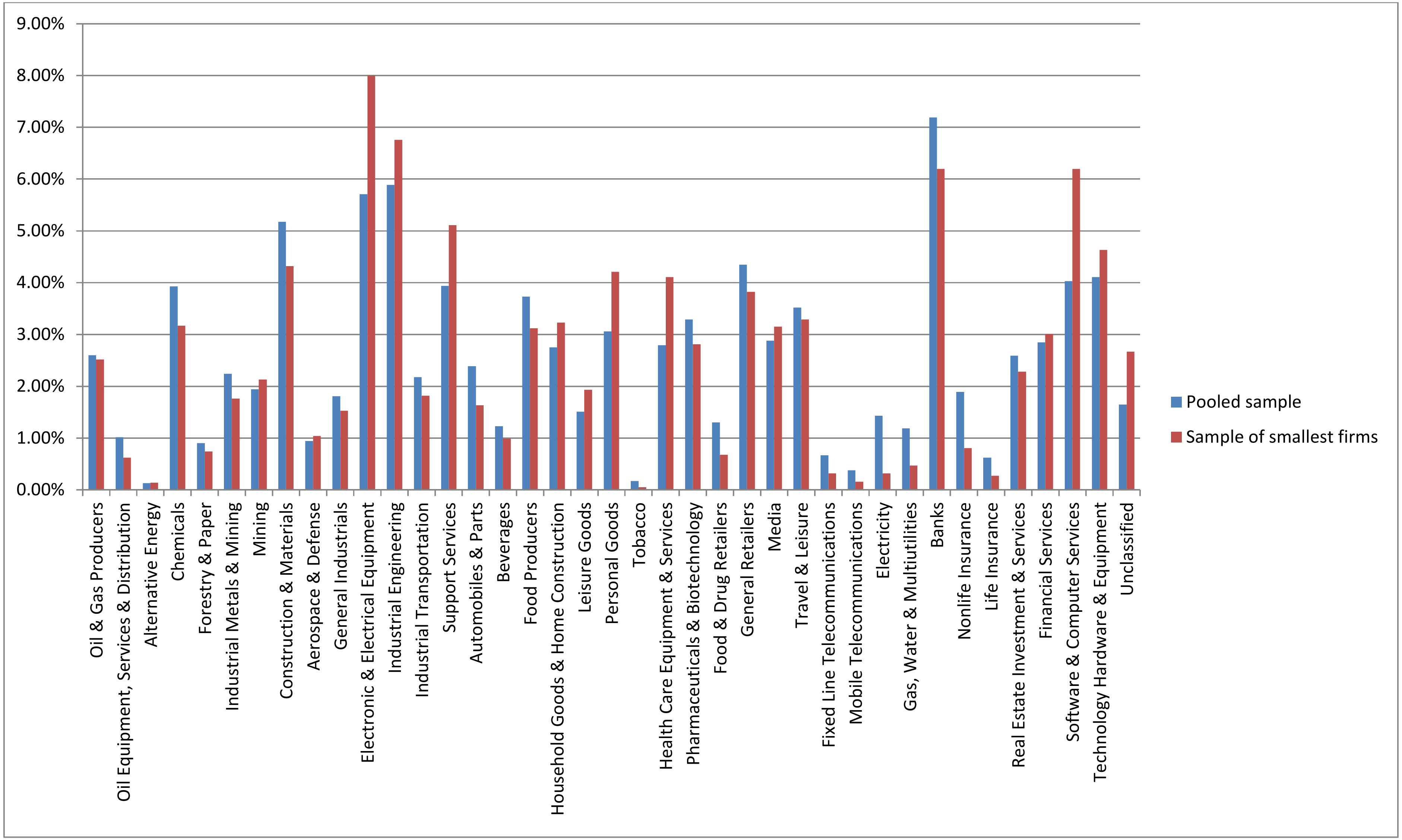

Figure 3
The simple average monthly return over the past year

The smallest(biggest) portfolio is the monthly updated portfolio containing the 10% smallest(biggest) stocks based on the beginning-of-the-month dollar market capitalization with breakpoints set on the pooled sample. The market portfolio is proxied by the TRD World Market Index.

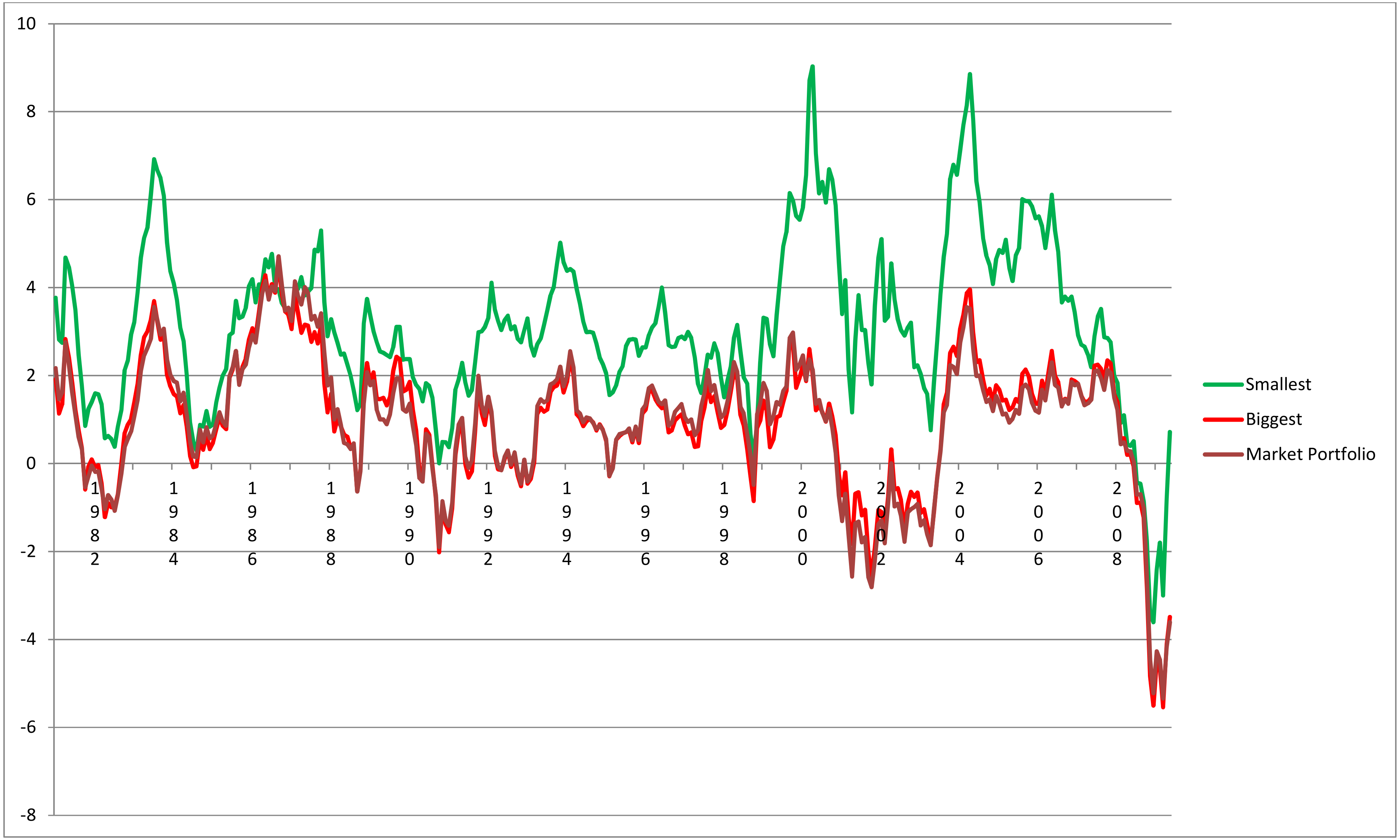

Figure 4

Average geographical distribution difference between the sample of smallest stocks and the pooled sample (in terms of number of firms)

This figure is the graphical representation of the difference between the last-but-one column and column 4 of Table 1. A smallest firm is defined as having its market capitalization in the first size decile of the pooled sample. The size breakpoints are updated monthly.

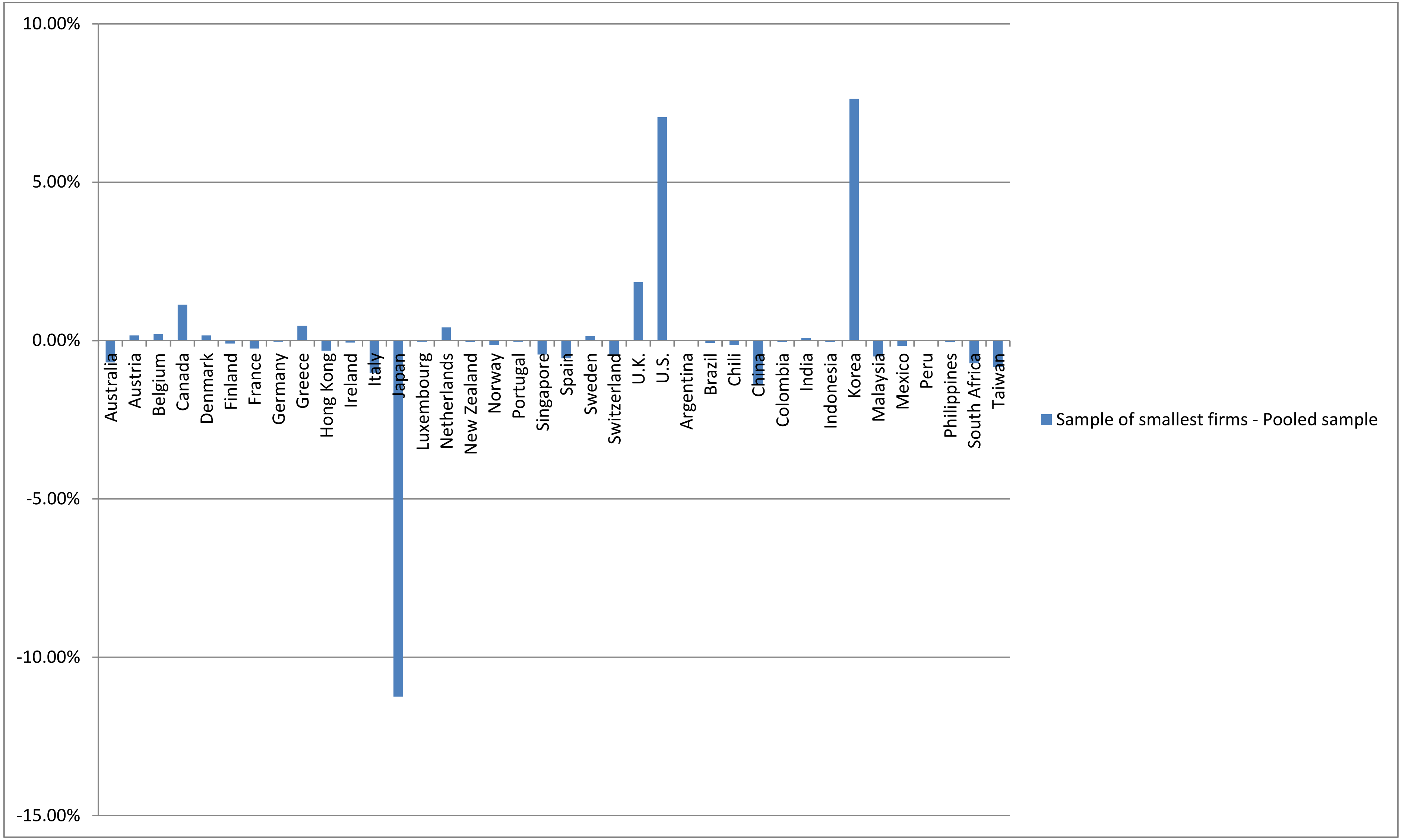

Figure 5
Sectorial distribution difference between of the sample of smallest stocks and the pooled sample

This figure is the graphical representation of the difference between the last-but-one column and column 4 of Table 2. A smallest firm is defined as having its market capitalization in the first size decile of the pooled sample. The size breakpoints are updated monthly.

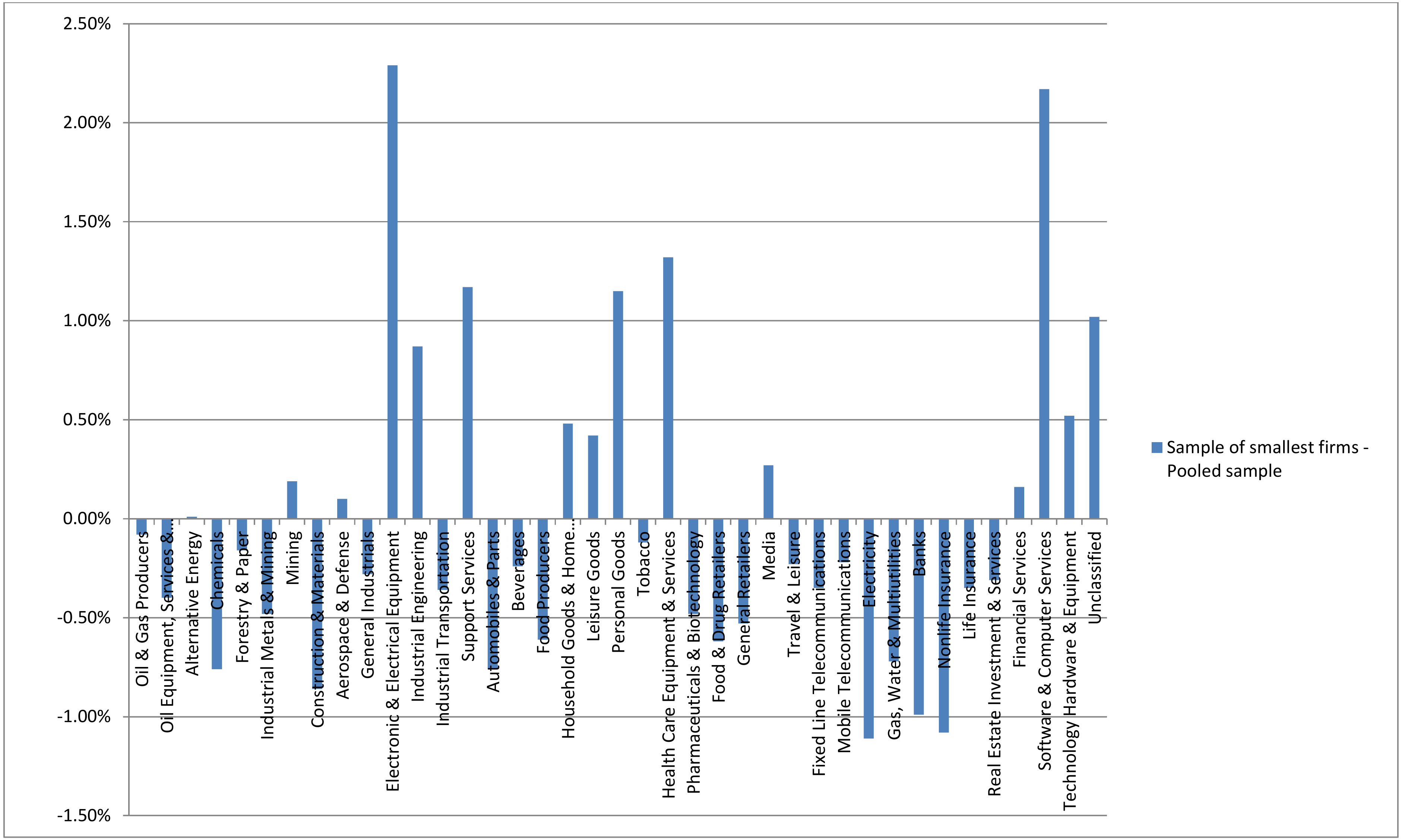

Figure 6
Average stock exchange distribution (in terms of number of ongoing firms)

This figure is the graphical representation of Table 4, only for the larger stock exchanges. The average stock exchange distribution is the time-series average, calculated over the full sample period, of the monthly ratio (in %): number of ongoing firms quoted on the selected stock exchange relative to the total number of ongoing firms. The larger stock exchanges are defined by having an above-1% weight in the pooled or smallest firm sample.

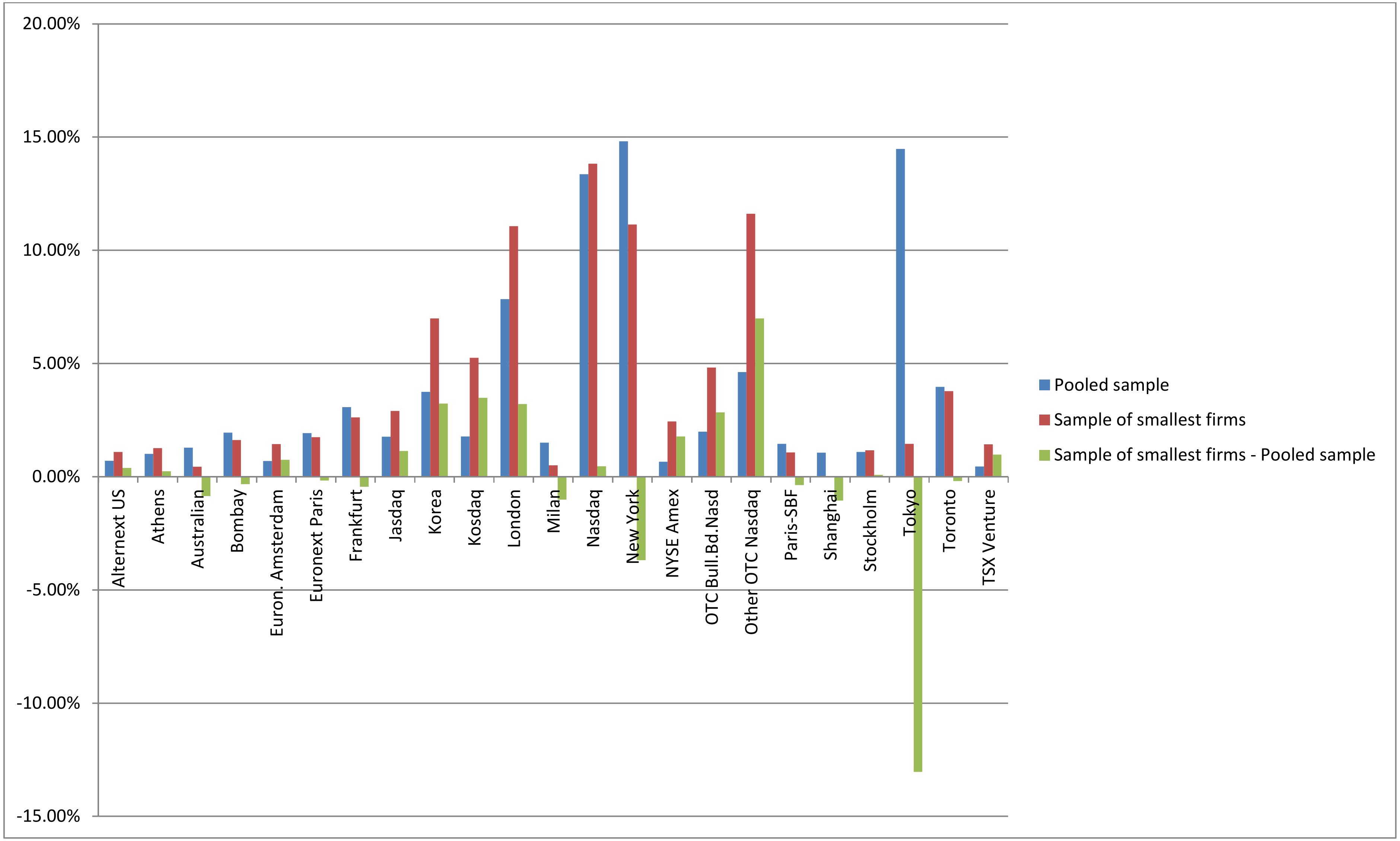

Figure 7

Currency distribution of pooled and smallest firm sample

This figure is the graphical representation of Table 15. The average currency distribution is the time-series average, calculated over the full sample period, of the monthly ratio (in %): number of ongoing firms quoted in the selected currency relative to the total number of ongoing firms. smallest firm is defined as having its market capitalization in the first size decile of the pooled sample. The size breakpoints are updated monthly.