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Risk factors and capital market anomalies
-
International evidence

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ABSTRACT

Capital market anomalies are empirical results that seem to be unexplained by the Capital Asset Pricing Model. The dissertation analyzes whether anomalies that previously existed also persist in new and independent samples. Patterns related to stock characteristics are also present in emerging market stock returns as well as in implied cost of capital of G-7 countries. Furthermore, it is explained why average momentum returns have historically been low in Japan, a fact generally referred to as an empirical failure of momentum.

ZUSAMMENFASSUNG

Kapitalmarktanomalien sind empirische Ergebnisse, die sich scheinbar nicht durch das Capital Asset Pricing Model erklären lassen. Die Dissertation analysiert, ob Anomalien, die in der Vergangenheit auftraten, auch in neuen und unabhängigen Stichproben fortbestehen. Unterschiede in Abhängigkeit von Aktiencharakteristika existieren sowohl für die Renditen von Schwellenländeraktien als auch für die impliziten Kapitalkosten der G-7 Länder. Desweiteren wird erklärt, warum Momentumrenditen in Japan bislang niedrig waren - eine Tatsache, die gemeinhin als ein Misserfolg von Momentum bezeichnet wird.

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ACRONYMS

ADRs	American depositary receipts
AMEX	American Stock Exchange
BBA	British Bankers' Association
B/M	book-to-market
BRIC	Brazil, Russia, India, and China
CAPM	Capital Asset Pricing Model
CARs	cumulative abnormal returns
CRSP	Center for Research in Security Prices
CT	implied cost of capital method based on Claus and Thomas (2001)
EM	emerging markets
EMEA	Europe, the Middle East, and Africa
EMDB	Emerging Markets Database
EPS	earnings per share
ETFs	exchange-traded funds
FF	Fama-French
FF3FM	Fama-French three-factor model
FROE	forecasted return on equity
GLS	implied cost of capital method based on Gebhardt, Lee, and Swaminathan (2001)
GRS	test statistic based on Gibbons, Ross, and Shanken (1989)
I/B/E/S	Institutional Brokers' Estimate System
ICB	Industry Classification Benchmark
ICC	implied cost of capital

IFC	International Finance Corporation
ISIN	International Securities Identification Number
JPY	Japanese Yen
KF	Kenneth French
LHS	left-hand side
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
MPEG	implied cost of capital method based on the modified price-earnings-growth ratio, proposed in Easton (2004)
MSCI	Morgan Stanley Capital International
MV	market value
OECD	Organization for Economic Co-operation and Development
OJ	implied cost of capital method based on Ohlson and Juettner-Nauroth (2005) and Gode and Mohanram (2003)
PACAP	Pacific-Basin Capital Markets
REITs	real estate investment trusts
RHS	right-hand side
ROE	return on equity
S&P	Standard & Poor's
T-bill	Treasury-bill
TR	Thomson Reuters
TRD	Thomson Reuters Datastream
U.K.	United Kingdom
U.S.	United States
USD	United States Dollar

B	big stocks
S	small stocks
H	high book-to-market stocks
N	neutral book-to-market stocks
L	low book-to-market or looser stocks
W	winner stocks
M	medium past performance stocks
L	looser stocks or low book-to-market stocks

RM	market return
RF	risk-free rate
RMRF	market excess return
SMB	small minus big, size factor based on Fama and French (1993)
HML	high minus low, value factor based on Fama and French (1993)
*W*ML	winner minus losers, momentum factor based on Carhart (1997)
MOM	momentum, momentum factor based on Jegadeesh and Titman (1993)

1 INTRODUCTION

1.1 MOTIVATION

Asset prices provide crucial information for the allocation of resources. Stock exchanges are one of the largest and most important markets for asset prices, e.g., the prices of common stocks. On the one hand, the price of a common stock displays how much an investor has to pay to acquire one unit of ownership in the underlying firm. This ownership entitles the investor to share in the profits and to vote at the general meeting of the company. On the other hand, equity securities serve as an instrument for the financing of the company's operations. The price of the security reflects the amount of money the firm can realize for selling one unit of common stock held by the firm. Therefore, an improved understanding of the behavior of stock prices is one of the most important research goals in finance. Understanding the behavior of prices means to understand the drivers of these prices and to explain the associated returns.

Explaining security returns requires understanding the underlying risks and determinants of the securities. The portfolio model in Markowitz (1959) illustrates that security specific risk can be diversified away and, therefore, investors should only be rewarded for systematic risk. But what are the systematic risk factors that affect security prices?

The Capital Asset Pricing Model (CAPM) was developed by Sharpe (1964), Lintner (1965), and Mossin (1966). According to the CAPM, the expected return of a security R_i consists of the risk-free rate R_f plus a risk premium for taking additional risk. This premium entirely depends on the comovement of the security i with the market portfolio.

Hence the beta of security i, b_i, defined as the standardized covariance of the security with the market portfolio, is the only measure of systematic risk. Additional variables, such as security characteristics, should not have an impact on the expected return.

First studies on the CAPM tried to explain the cross-sectional variation of stock returns. Black et al. (1972) and Fama and MacBeth (1973) verify the positive influence of beta on realized returns; however, the results indicate that the relation is too flat. Therefore, the CAPM underestimates the returns of low beta stocks and overestimates the returns of high beta stocks. These results are inconsistent with the Sharpe-Lintner-Mossin CAPM, but more compatible with the zero-beta CAPM introduced by Black (1972).[1]

Further tests, however, indicated that variables other than beta also influence average stock returns. Basu (1977) shows that stocks that exhibit high earnings-price ratios have higher returns than predicted by the CAPM. Similar results hold for stocks with low market capitalization (Banz, 1981) or high book-to-market ratios (Rosenberg et al., 1985).[2] High returns for stocks with these characteristics are not a problem per se for the CAPM. The problem is that the betas of these stocks are not high enough to capture these high returns. Because these patterns seem to be unexplained by the CAPM, they are called capital market anomalies.

Fama and French (1992) confirm the earlier evidence of empirical failures of the CAPM. Using Fama and MacBeth (1973) cross-sectional regressions, they demonstrate that size and book-to-market explain the cross-sectional differences associated with size, book-to-market,

1 This finding was the starting point for a line of research investigating the relationship between risk and return in the cross-section of securities. See, e.g., Haugen and Heins (1975), Haugen and Baker (1996), Ang et al. (2006), Blitz and Vliet (2007), Ang et al. (2009b), Blitz et al. (2013), or Frazzini and Pedersen (2014).

2 Within this line of literature, the book-to-market ratio is always defined as the ratio of the book value of common equity to its market value. Thereby, the market value of equity is the market capitalization of the common stocks, i.e., the number of securities outstanding times the price of a common stock. The book value of common equity is derived from the balance sheet.

earnings-price, and leverage, whereas the relation between beta and average returns is weak.[3]

Building on these results, Fama and French (1993) add two additional return factors to the CAPM to capture the cross-section of stock returns. The two factors are zero-cost portfolios related to size and book-to-market. The so-called Fama-French three-factor model captures cross-sectional patterns in portfolios sorted by size and book-to-market better than the CAPM. Furthermore, the three-factor model was also able to explain return differences associated with other characteristics, such as price-earnings ratio, price-cash flow-ratio, past sales growth, and long-term past returns, as demonstrated in Fama and French (1996).[4] Only the continuation of medium-term past returns, discovered by Jegadeesh and Titman (1993), could not be captured.[5] Therefore, Carhart (1997) extends the model by another factor related to the medium-term past performance of common stocks to explain the difference between the average returns on winner and loser stocks. The high explanatory power for different sorting schemes is the reason why the Fama-French three-factor model or the Carhart four-factor model are still the "industry standard" (Subrahmanyam, 2010, p. 35) in empirical asset pricing.

Fama and French (1996) identify three main arguments for the explanatory power of the two additional factors. The first explanation is that the factors related to size and book-to-market are proxies for additional risk factors not captured by the CAPM. The underlying risks are not obvious but Fama and French (1993) and Fama and French (1996) interpret the high returns of small capitalization and

3 Within this thesis, the term size refers to the market capitalization of common stocks and I use the two terms interchangeably.

4 As the book-to-market factor captures the cross-section return differences related to other value strategies, it is also called the value factor. These value strategies have the following in common: they buy stocks with low prices and sell stocks with high prices relative to a fundamental. They are denoted as value strategies as they intend to buy securities that appear to have good value to some fundamental. In contrast, stocks with high prices relative to a fundamental are called growth or glamour stocks.

5 Beside size and value, the continuation of medium-term past returns, momentum, is one of the "big three" anomalies in empirical asset pricing.

high book-to-market stocks as a premium that investors expect for relative distress risk which is not part a of beta. Consequently, the CAPM has to be discarded and replaced by a multifactor model including these risk proxies. This does not mean that the CAPM is useless. However, the CAPM is based on certain unrealistic assumptions. For example, the assumptions of complete information of market participants and frictionless markets are far from reality. Therefore, the CAPM is a good starting point for an asset pricing model and it can be improved to become a model that better captures the variation in expected returns.[6]

The second explanation accepts the higher explanatory power of the multifactor model, but argues that mispricing, and not risk, leads to the rejection of the CAPM. Lakonishok et al. (1994) are proponents of this view. They argue that investors extrapolate past performance too far into the future and, therefore, stocks with low growth rates in the past tend to have low market values relative to fundamentals, and vice versa. However, differences in future growth rates based on past growth rates are overestimated and value stocks, such as stocks with high book-to-market ratio, outperform glamour stocks when future growth rates become visible. Hence the market is not efficient and the higher returns associated with size and with book-to-market, in particular, are the result of systematic mispricing.

The third explanation in Fama and French (1996) is that the empirical evidence is spurious because of survivorship bias, bad proxies for the market portfolio, or, simply, data snooping. Kothari et al. (1995) argue that the returns of high book-to-market portfolios in Fama and French (1993) are overstated as Compustat is more likely to contain stocks within these portfolios that survived than delisted stocks with poor performance. While Chan et al. (1995) and La Porta (1996) directly counter the survivorship bias arguments, criticism regarding data snooping can never be excluded.

6 See Fama and French (2004).

The CAPM assumes that the market portfolio consists of all marketable assets. However, the exact composition of the true market portfolio is unknown.[7] Most studies approximate the market portfolio with a value-weighted portfolio of all stocks within their sample. Other risky assets, such as bonds, commodities, human capital, or real estate are not included. Therefore, the critique is that the CAPM holds and the anomalies are the result of the shortcomings of the proxies for the market portfolio. Fama and French (1996) emphasize that this critique does not justify the way the CAPM is currently applied, as the market proxies in these applications are usually the same as in the anomalies literature. The spurious anomalies of the CAPM also result in problems for applications, such as cost of capital estimation or performance evaluation. The additional risk factors potentially help to overcome the shortcomings of the used market portfolio. Therefore, multifactor models provide better estimates for the expected returns of common stock.

Data snooping means that, ex post, one always finds some deviations from the CAPM by dredging up a given dataset.[8] By grouping these observations into portfolios, the deviations appear statistically significant; however, only because the disturbances and sorting criteria are correlated.[9] Consequently, repeated tests on nearly the same data samples and the same data treating conventions lead to the same results. Therefore, out-of-sample tests are needed to rebut the data snooping criticism.

Schwert (2003) highlights that "the key test is whether the anomaly persists in new, independent samples" (p. 941). Persistence in younger data samples is important, as there are two explanations for why anomalies that previously existed could disappear after their documentation; beside data snooping, these opportunities could be arbitraged away by investors trying to harvest the documented "abnormal" returns. Therefore, new and younger samples have the addi-

7 See Roll (1977).
8 See MacKinlay (1995).
9 See Lo and MacKinlay (1990).

tional advantage of testing whether the anomalies lived on in periods that are more recent. Consequently, this dissertation focuses on two samples previously less researched than others, and on one observation that is regarded as an empirical failure of one of the three big anomalies.

1.2 STRUCTURE OF THE THESIS AND CONTRIBUTION

Next to the introduction and the outline in this chapter, Chapter 2 presents details about the sample definition, data quality screens, and portfolio construction using Thomson Reuters (TR) as the data provider for the analysis in subsequent chapters. Furthermore, I provide evidence that these steps lead to comparable results for my and international benchmark factors. The following main body of the dissertations consists of three chapters, each of which is a distinct research contribution (Chapters 3 to 5). While Chapters 3 and 5 focus on two samples previously less researched than others, Chapter 4 focuses on one observation that is regarded as an empirical failure of one the anomalies. Moreover, each of the three chapters makes independent academic contributions of its own.[10]

The majority of studies analyze the United States (U.S.). One of the reasons for this dominance, beside the importance and weight of the U.S. market, is data availability. For most of the above-cited studies, the Center for Research in Security Prices (CRSP) provided the analyzed data which is perceived to be high quality. However, CRSP primarily covers the North American stock markets. For international data on the cross-section of stock returns, TR is the most significant data provider.

10 Within these chapters, I address the relevant literature for the distinct research question. For comprehensive literature reviews, the interested reader is referred to some excellent surveys: van Dijk (2011) provides a comprehensive review of the size effect, Richardson et al. (2010) for accounting anomalies, Jegadeesh and Titman (2011) for momentum, Subrahmanyam (2010) for the cross-section of stock returns, Subrahmanyam (2008) for behavioral finance, and Goyal (2012) for econometric methods.

As Ince and Porter (2006) describe, raw return data from Thomson Reuters Datastream (TRD) may not be error-free. Therefore, it is essential to assure data quality when using data from TRD. Chapter 2 details sample definition, data quality screens, and portfolio construction.

Initial studies analyzing developed markets outside the U.S. mainly confirm the size, value, and momentum patterns found for the U.S. for similar time frames.[11] However, under the hypothesis that developed markets are integrated, the same risk factors should apply to these markets. Therefore, similar results for similar time periods are not surprising.

Emerging market samples provide an attractive alternative for out-of-sample tests in terms of independent and new samples compared to developed markets samples. Data availability for emerging markets starts about the same time as the sample period of the initial U.S. studies ends.[12] This offers the possibility to test whether the anomalies persist after their documentation in the literature.

Although the importance of emerging market economies and stock markets is constantly rising,[13] few studies have investigated the size, value, and momentum effects in emerging markets. Therefore, I provide a detailed analysis for a broad set of emerging markets countries in a methodologically consistent way in Chapter 3.

Furthermore, I discuss integrated global pricing for emerging markets to examine whether emerging markets pricing is segmented or integrated. Therefore, I conduct asset pricing tests of global and local versions of the CAPM, three-factor and four-factor asset pricing models on emerging markets portfolios. If emerging markets are in-

11 See, e.g., Chan et al. (1991), Daniel et al. (2001), Griffin (2002), Liew and Vassalou (2000) and Rouwenhorst (1998).

12 For example, Morgan Stanley Capital International (MSCI) first published comprehensive emerging market indices go back to 1988, whereas data series for Eastern European or the comprising economies of Brazil, Russia, India, and China (BRIC) go back to 1995. The period covered in Fama and French (1993) is 1963 to 1991.

13 The Organization for Economic Co-operation and Development (OECD) estimates a dramatic change in the relative size of economies within the next 50 years, a shift toward emerging countries (Johansson et al., 2012).

tegrated, the global models should perform as well as the local ones or better.

In Chapter 4, I investigate a fact generally referred to as an empirical failure of one of the three big anomalies, momentum. Despite the broad evidence of momentum profits around the world, there is one remarkable exception. Several studies argue that momentum strategies fail in Japan as they do not find any significant premium (e.g., Griffin et al., 2003; Fama and French, 2012; Asness et al., 2013) or even observe a negative mean return (Chou et al., 2007). Although these results could be rejected as bad luck, there are other explanations for why momentum returns are smaller in Japan or why momentum should not be considered alone. Chui et al. (2010) argue that momentum returns are weaker in countries with low individualism such as Japan or other parts of Asia. In contrast, Asness (2011) argues that momentum should be studied in a system with value because they are negatively correlated.

As opposed to the majority of studies on momentum, I focus on momentum profits under different market dynamics. According to the behavioral model of Daniel et al. (1998), investors' overconfidence is expected to be higher when the market remains in the same state than when it reverses. Therefore, momentum returns should be higher in market continuations than in market transitions. Asem and Tian (2010) provide mixed evidence, because they can present this pattern for the U.S. but not for Japan.

I examine a comprehensive and carefully screened dataset to explore if market-dynamic conditional momentum is also present in the Japanese stock market. Furthermore, I provide a potential explanation for why this pattern is more pronounced after periods of poor market performance.

Chapter 5 focuses on expected returns, as asset pricing models typically build on expected returns. Consequently, to test the empirical validity of an asset pricing model one has to find a reasonable proxy for expected returns. Due to the difficulties in observing expectations, realized returns are thus far the most common proxy in empirical studies that test asset pricing models.

The implied cost of capital (ICC), which is defined as the discount rate that matches analyst earnings forecasts with the current stock price, has several advantages over observed returns, which have recently come under criticism.[14] First, Elton (1999) argues that realized returns are a poor measure of expected returns because they are notoriously noisy. In contrast, the standard deviation of the ICC is an order of magnitude smaller than the standard deviation of realized returns. Moreover, realized returns cannot be decomposed into a discount rate part and a cash flow news part. In contrast, the ICC directly accounts for cash flow news by using time-varying analyst earnings forecasts. Consequently, the ICC reflects only the discount rate part. Finally, the ICC is conditional on the current state of the economy and, therefore, is able to reflect return expectations in line with investors' current risk aversion and should be useful in capturing time variation in expected returns. However, realized and expected returns are negatively related in the short run since innovations in expected returns cause ex post returns to move in the opposite direction.

These arguments motivated various studies in finance to use the ICC as an expected return estimate. Both theoretical considerations and empirical evidence indicate that the ICC can shed new light on evidence previously based on realized returns data.

To the best of my knowledge, the explanatory power of the Fama-French three-factor model has only been evaluated using realized returns. Instead, I am the first to validate this model utilizing the ICC. Thus, my main contribution is providing evidence about the relevant risk factors and the appropriate asset pricing model using an alternative expected return proxy.

Therefore, I compute firm-level ICC for an international dataset comprising the G-7 countries, i.e., Canada, France, Germany, Italy,

14 Within this thesis, I use the term cost of capital to describe the cost of common equity, to be precise.

Japan, the United Kingdom (U.K.), and the United States (U.S.), using analyst earnings forecasts provided by Institutional Brokers' Estimate System (I/B/E/S). I then determine the expected risk premiums computed from those ICC and re-run the analysis of Fama and French (1993) for the seven countries. Therefore, using the ICC instead of realized returns is another out-of-sample test.

Chapter 6 summarizes the main results of the thesis and discusses their implications for both researchers and practitioners.

2

SAMPLE DEFINITION, DATA QUALITY, AND PORTFOLIO CONSTRUCTION

Till date, the majority of empirical asset pricing studies analyze the United States (U.S.). One of the reasons for this dominance, beside the importance and weight of the U.S. market, is data availability. The Center for Research in Security Prices (CRSP) provides time-series data going back to 1926 for the New York Stock Exchange (NYSE), to 1962 for the American Stock Exchange[15] (AMEX), and to 1972 for the National Association of Securities Dealers Automated Quotations (NASDAQ).[16] CRSP is perceived as a high-quality data provider and the data quality has been examined first by Rosenberg and Houglet (1974) and later by Bennin (1980). Furthermore, continuous efforts are made to check and improve data quality.[17] Together with the link to balance sheet information on Compustat, CRSP is typically used for studies on the U.S. market. The drawback of the extensive use of this dataset is that the results could be driven by data snooping.[18] Out-of-sample tests present a solution to address data-related criticism. Testing persistence in out-of-sample data for the U.S. is one possibility. However, older data may be hard to obtain or subject to data quality issues while it takes considerable time to gather new out-of-sample data that is statistically reliable. Therefore, focusing on other (international) markets is an alternative solution. This chapter presents details about sample definition, data quality screens, and portfolio construction using Thomson Reuters Datastream (TRD) as data source for out-of-sample tests. Furthermore, I provide evidence

15 In 2008, NYSE Euronext acquired the American Stock Exchange and re-branded it to NYSE MKT.
16 See Center for Research in Security Prices (2012).
17 See Center for Research in Security Prices (2012).
18 See Lo and MacKinlay (1990) and MacKinlay (1995) for more detailed information.

that the application of these steps leads to risk factors that are highly comparable to the risk factors provided by Kenneth French's data library for the U.S. and global developed markets. These risk factors are constructed as in Fama and French (1993) and Fama and French (2012).

2.1 SAMPLE DEFINITION

Appropriate samples for cross-sectional analysis should not suffer from survivorship bias. Otherwise the results could be distorted by a certain group of stocks that was exposed to some high risks (represented by a certain characteristic) but survived and is included in the sample. These survivors are rewarded with high past returns. The non-surviving stocks (with similar characteristics) disappeared from the sample, accompanied with low returns that are subsequently missing in the sample. Backtests that group stocks on such a characteristic from samples with survivorship bias overstate the returns for portfolios exposed to risks proxied by this characteristic, as only the high returns of the survivors are included but not the missing low returns. Current constituent lists from index providers typically suffer from survivorship bias.

To address this problem, some studies built upon hand-collected datasets, updated on a continual basis, or upon national data providers covering certain exchanges or market segments. Examples for this approach outside the U.S. are L'Her et al. (2004) for Canada; Schrimpf et al. (2007), Artmann et al. (2012), and Hanauer et al. (2013) for Germany; Chan et al. (1991) and Daniel et al. (2001) for Japan; Waszczuk (2013) for Poland; Ammann and Steiner (2008) for Switzerland; and Gregory et al. (2013) for the U.K. As noted by Schmidt et al. (2010), these country-specific datasets are generally not accessible to other researchers or are not comparable in terms of time and market coverage or data quality.

Thomson Reuters (TR) is a data provider covering price data and fundamentals for more than 100 and 75 countries, respectively.[19] It is used for studies on developed markets (e.g., Liew and Vassalou, 2000; Griffin, 2002; Schmidt et al., 2010), emerging markets (Cakici et al., 2013), and both developed and emerging markets (Griffin et al., 2003, 2010; Chui et al., 2010; Hou et al., 2011). Besides TR, some other data vendors exist. The Sandra Ann Morsilli Pacific-Basin Capital Markets (PACAP) Research Center provides data for eight Asian markets and is used in Daniel et al. (2001) (Japan) and Lam et al. (2010) (Hong Kong), inter alia. Fama and French (1998) and Fama and French (2006) use Morgan Stanley Capital International (MSCI) data for countries other than the U.S. For emerging market studies, Rouwenhorst (1999) and van der Hart et al. (2003) use the Emerging Markets Database (EMDB) of the International Finance Corporation (IFC), whereas Blitz et al. (2013) use only a subset of this index, the S&P/IFC Investable Emerging Markets Index.[20] However, Fama and French (2012) mention that the sample used in Fama and French (1998) and Fama and French (2006) is thin on small stocks and van der Hart et al. (2003) state that EMDB is also biased toward larger stocks.[21] Hence, these two datasets may be representative of stocks suitable for trading strategies; however, they do not qualify for certain out-of-sample tests, e.g., the size effect, as exactly the bottom 10% of aggregated market capitalization within CRSP represents the group of the small stocks.[22] The data used in Fama and French (2012) primarily comes from Bloomberg, supplemented by Datastream and Worldscope.

In contrast to CRSP, TRD does not provide time-varying information about the listing of a stock. For studies using more than one country, usually all stocks within a market segment meeting certain criteria are selected.

19 See Thomson Reuters (2013b) and Thomson Reuters (2013a).
20 S&P denotes for Standard & Poor’s.
21 For example, MSCI targets to cover 80 % of the market capitalization of a region.
22 See section 2.4.3.

I identify stocks by Thomson Reuters Datastream's constituent lists for a certain country and follow the suggestions of Ince and Porter (2006), Griffin et al. (2010), and Schmidt et al. (2010). The screens to assure data quality are explained in more detail within the next subsection. To avoid a survivorship bias, I use the intersection of Datastream research lists, Worldscope lists, and dead lists for each of the 45 regarded countries. In accordance with the MSCI classification, the following countries are labeled as developed market countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States.[23] Furthermore, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Peru, Philippines, Poland, Russia, South Africa, South Korea, Taiwan, Thailand, and Turkey are classified as emerging market countries.[24] Table 1 and Table 2 present the utilized constituents lists for developed and emerging market countries, respectively[25]

I restrict my sample to stocks of type equity (TYPE="EQ"); companies and securities located and listed in the domestic country (e.g., for the U.S.: GEOGN=GEOLN="UNITED STATES"); the primary quotation of a security (ISINID="P"); and the security with the biggest market capitalization and liquidity for companies with more than one equity security (MAJOR="Y"). Furthermore, I exclude securities with quoted currency and ISIN country code other than these of the respective country (e.g., for the U.S.: PCUR="U$" and GGISN="US").[26]

23 In 2013, MSCI announced that Greece will be reclassified as an emerging market country in November 2013. As my analysis covers the period as Greece was classified as developed market country, I keep Greece in my developed market sample.
24 See, MSCI Inc. (2012a).
25 Please note that the constituents lists are continuously updated.
26 For the countries of the euro area, also the respective pre-euro currency is treated as a domestic currency beside the euro. The same applies for securities with quoted currency equal to United States Dollar (USD) in Russia. Furthermore, I do not exclude securities with an International Securities Identification Number (ISIN) country code equal to "BM" or "KY" for Hong Kong and "CS" for the Czech Republic.

While some studies exclude financials, such as banks or insurance companies, from their sample due to different accounting standards and valuation methods (e.g., Fama and French, 1992; Griffin, 2002; Schrimpf et al., 2007; Lam et al., 2010; Artmann et al., 2012; Gregory et al., 2013; Hanauer et al., 2013; Waszczuk, 2013), the majority of international studies include this sector (e.g., Chan et al., 1991; Fama and French, 1993, 1996, 1998, 2006, 2012; Jegadeesh and Titman, 1993, 2001; Liew and Vassalou, 2000; Daniel et al., 2001; Griffin et al., 2003, 2010; L'Her et al., 2004; Ammann and Steiner, 2008; Chui et al., 2010; Cakici et al., 2013). In this thesis, I will follow the second approach as I primarily use international data and I want the assure comparability to the risk factors as calculated as in Fama and French (1993) and Fama and French (2012).

Table 1: **Constituent lists: Developed markets**
I use Thomson Reuters Datastream's constituent lists to build my sample of common stocks. To avoid a survivorship bias, I use the intersection of Datastream research lists, Worldscope lists, and dead lists for each of the 45 regarded countries. The table presents the identifiers of the constituent lists of the 24 developed market countries.

Country	Lists	Country	Lists
Australia	DEADAU	**Japan**	DEADJP
	WSCOPEAU		WSCOPEJP
	FAUS		FJAP
Austria	DEADOE		FTOKYO
	WSCOPEOE		FOSAKA
	FOST		FJASDAQ
Belgium	DEADBG	**Netherlands**	DEADNL
	WSCOPEBG		WSCOPENL
	FBDO		FHOL
	FBEL	**New Zealand**	DEADNZ
Canada	DEADCN1		WSCOPENZ
	DEADCN2		FNWZ
	WSCOPECN	**Norway**	DEADNW
	FVANC		WSCOPENW
	FTORO		FNOR
Denmark	DEADDK	**Portugal**	DEADPT
	WSCOPEDK		WSCOPEPT
	FDEN		FPOR
Finland	DEADFN		FPOM
	WSCOPEFN		FPSM
	FFIN	**Singapore**	DEADSG
France	DEADFR		WSCOPESG
	WSCOPEFR		FSIN
	FFRA		FSINQ
Germany	DEADBD1	**Spain**	DEADES
	DEADBD2		WSCOPEES
	DEADBD3		FSPN
	WSCOPEBD		FSPNQ
	FGERDOM		FSPDOM
Greece	DEADGR	**Sweden**	DEADSD
	WSCOPEGR		WSCOPESD
	FGRMM		FSWD
	FNEXA	**Switzerland**	DEADSW
	FGRPM		WSCOPESW
	FGREE		FSWS
Hong Kong	DEADHK		FSWA
	WSCOPEHK	**Unit. Kingdom**	DEADUK
	FHK1		WSCOPEUK
	FHK2		FBRIT
	FHKQ	**Unit. States**	DEADUS1 - DEADUS6
Ireland	DEADIR		WSUS1 - WSUS20
	WSCOPEIR		FUSAA - FUSAG
	FIRL		
Italy	DEADIT		
	WSCOPEIT		
	FITA		

Table 2: **Constituent lists: Emerging markets**
I use Thomson Reuters Datastream's constituent lists to build my sample of common stocks. To avoid a survivorship bias, I use the intersection of Datastream research lists, Worldscope lists, and dead lists for each of the 45 regarded countries. The table presents the identifiers of the constituent lists of the 21 emerging market countries.

Country	Lists	Country	Lists
Brazil	DEADBRA	**Morocco**	DEADMOR
	WSCOPEBR		WSCOPEMC
	FBRA		FMOR
	DEADCHI	**Peru**	DEADPE
Chile	WSCOPECL		WSCOPEPE
	FCHILE		FPERU
	DEADCH	**Philippines**	DEADPH
China	WSCOPECH		WSCOPEPH
	FCHINA		FPHI
Colombia	DEADCO		FPHIQ
	WSCOPECB	**Poland**	DEADPO
	FCOL		WSCOPEPO
Czech Republic	DEADCZ		FPOL
	WSCOPECZ	**Russia**	DEADRU
	FCZECH		WSCOPERS
Egypt	DEADEGY		FRUS
	WSCOPEEY	**South Africa**	DEADSAF
	FEGYPT		WSCOPESA
Hungary	DEADHU		FSAF
	WSCOPEHN	**South Korea**	DEADKO
	FHUN		WSCOPEKO
India	DEADIND		FKOR
	WSCOPEIN	**Taiwan**	DEADTW
	FINDIA		WSCOPETA
	DEADIDN		FTAI
Indonesia	WSCOPEID		FTAIQ
	FINO	**Thailand**	DEADTH
Malaysia	DEADMY		WSCOPETH
	WSCOPEMY		FTHA
	FMAL		FTHAQ
	FMALQ	**Turkey**	DEADTK
Mexico	DEADME		WSCOPETK
	WSCOPEMX		FTURK
	FMEX		

2.2 DATA QUALITY

Thomson Reuters offers stock market data via Datastream, while accounting data can be accessed via Worldscope. Studies defining their sample with other data sources obtain return and accounting data from the particular data source (Schrimpf et al., 2007; Artmann et al., 2012; Gregory et al., 2013; Waszczuk, 2013) or merge their sample with data from TRD (Hanauer et al., 2013) or Factset (Ammann and Steiner, 2008).

As Ince and Porter (2006) describe, raw return data from TRD may not be error-free. Following Ince and Porter (2006), Griffin et al. (2010), and Schmidt et al. (2010), I apply several screens to ensure data quality. The static screens ensure that the sample contains only common equity stocks in a country, whereas dynamic screens are applied on the monthly return data.

2.2.1 *Static screens*

Ince and Porter (2006) report that TRD includes many securities with TYPE equal to "EQ" that are not common stock, such as American depositary receipts (ADRs), closed-end funds, exchange-traded funds (ETFs), and real estate investment trusts (REITs). They suspect that these non-common equity securities could especially affect the returns of portfolios sorted by size. To eliminate non-common equity securities, I search, similar to Ince and Porter (2006) and Griffin et al. (2010), for suspicious words in the company name, indicating that the security is a duplicate, preferred stock, debt, etc. Generic keywords for all countries are listed in Table 3. If a part of a security's name matches a generic keyword, the security is better classified to the category listed in the first column of Table 3 and not as common equity. The keywords of Table 4 are country-specific and only the names of the stocks of the corresponding country are matched to these keywords. The determination of these keywords is a gradual process. Copying the lists from Ince and Porter (2006) and Griffin et al. (2010) does not work, as many regular common stocks would also be eliminated. Based on my actual output of securities from TRD, I refine the keywords repeatedly to arrive at my final keywords.[27] A good example is the generic filter keyword "UT", which indicates that a security is a Unit Trust. But using "UT" would also suspect securities with the element "SOUTH" in their name as non-common equity securities. With the knowledge of the output names, the keyword is further developed to " UT " including two blank characters. The process creates a candidate list of firms for deletion. After a manual review, the identified securities are removed from the sample.

2.2.2 *Dynamic screens*

For the securities remaining from the static screens above, I obtain return and market capitalization data from Datastream and accounting data from Worldscope. Ince and Porter (2006) point out that raw return data from TRD could especially affect size and momentum portfolio returns. For example, Datastream repeats the last valid data point, e.g., the stock price, for a delisted stock after the delisting. This fact could, for instance, lead a delisted stock to incorrectly appear in a winner portfolio when the overall market is down, as it seems to outperform the market.

To address these problems, I calculate returns from the total return index and delete all zero returns (in local currency) from the end of the time-series to the first non-zero return. In addition, I remove all observations for which the return is greater than 890%, the unadjusted price in local currency is greater than 1,000,000 or the R_t or R_{t-1} is greater than 300%, and $(1+R_t)(1+R_{t-1})-1$ is smaller than 50%.

27 I thank Martin Linhart for excellent research assistance.

Table 3: **Generic filter rules to exclude non-common equity securities**
The table lists generic keywords for all regions, which serve as indicators that a Datastream security is, in contrast to its stock classification in Datastream, not common equity. If a part of a security's name matches a generic keyword, the security is better classified to the category listed in the first column of the same row and not as common equity. After a manual review, the identified securities are removed from the sample.

Non-common equity	**Keywords**
Duplicates	"DUPLICATE" " DUPL" "DUP." "DUPE" "DULP" "DUPLI" "1000DUPL" "XSQ" "XETa" " DUP " "DUPL "
Depository Receipts	" ADR" "GDR"
Preferred Stock	"Stock" "PREFERRED" "PF." "PFD" "PREF" "'PF'" "PRF"
Warrants	"WARRANT" "WARRANTS" "WTS" "WTS2" "WARRT"
Debt	" DEB " " DB" "DCB" " DEBT " "DEBENTURES" " DEBENTURE" "BOND" "%"
Unit Trusts (2 words)	"RLST IT" "INVESTMENT TRUST" "INV TST" "UNIT TRUST" "UNT TST" "TRUST UNITS" "TST UNITS" "TRUST UNIT" "TST UNIT"
Unit Trusts (1 word)	" UT " ".IT"
ETF	"ETF" "ISHARES" "INAV" "X-TR" "LYXOR" "JUNGE" "AMUNDI"
Ince and Porter (2006)	"500" " BOND " "DEFER" " DEP " "DEPY" "ELKS" " ETF" "FUND" "FD" "IDX" "INDEX" " MIPS" " MITS" "MITS." " MITT " " MITT." "NIKKEI" " NOTE." " NOTE " "PERQS" " PINES " " PINES." "PRTF" "PTNS" "PTSHP" "QUIBS" " QUIDS" " RATE" "RCPTS" "RECEIPTS" "REIT" "RETUR" " SCORE" "SPDR" "STRYPES" "TOPRS" "WTS" "XXXXX" "YIELD" "YLD" " QUIDS"
Expired securities	"EXPIRED" "EXPD" "EXPIRY" "EXPY"

Ince and Porter (2006) and Schmidt et al. (2010) delete stocks with unadjusted price in local currency less than 1.00. The reason is the discreteness of TRD output numbers and associated problems in calculating returns when prices are small. The same problem applies for low levels of the corresponding return index. However, internally TRD offers a higher resolution of prices. Therefore, I calculate percentage changes of the return index using the function "PCH#(X(RI),-1M)" and do not remove "penny stocks" from my samples.

2.3 CURRENCY

National studies usually calculate returns in domestic currency.[28] In contrast, for international studies USD returns are calculated to allow comparability.[29] For returns measured in USD, the one-month Treasury-bill (T-bill) rate is usually the proxy for the risk-free rate. For other return currencies one-month interbank rates offered by the British Bankers' Association (BBA) are used.

Therefore, I measure returns in USD of international markets in Chapter 3 and in Japanese Yen (JPY) for the calculation of risk factor returns in Japan in Chapter 4. In Chapter 5, I use values in domestic currency for the construction of implied risk premiums as I do not want to make assumptions about exchange rate forecasts to convert forecasted local currency earnings into USD.

28 See, e.g., Chan et al. (1991), Daniel et al. (2001), L'Her et al. (2004), Schrimpf et al. (2007), Ammann and Steiner (2008), Lam et al. (2010), Artmann et al. (2012), Hanauer et al. (2013), and Waszczuk (2013).

29 See, e.g., Liew and Vassalou (2000), Griffin (2002), Griffin et al. (2003), Griffin et al. (2010), Fama and French (1998), Fama and French (2006), Fama and French (2012), Hou et al. (2011), and Cakici et al. (2013).

Table 4: **Country-specific filter rules to exclude non-common equity securities**
The table lists country-specific keywords, which serve as indicators, that a Datastream security is, in contrast to its stock classification in Datastream, not common equity. If a part of the security's name matches one of its country-specific keywords from the second column, the security is better classified not as common equity. After a manual review, the identified securities are removed from the sample.

Country	**Keywords**
Developed Markets	
Australia	" RTS" " DEF" "DFD" "PAID" "PRF"
Austria	" PC" ".PC" "GSH" "Genussscheine"
Belgium	"CONV" "VVPR" "STRIP"
Canada	".RTS" " RTS" "SHS" "VTG" "SBVTG" "SUBD" "SR." "SER." "RECPT" "Receipt" "EXH" "EXCHANGEABLE" "SPLIT"
Denmark	"VXX" "CSE"
Finland	" USE "
France	"ADP" " CI " "CI." " CIP " "CIP." " ORA " " ORA." "ORCI" "OBSA" "OPCSM" "SGP" "SICAV" "FCP" "FCPR" "FCPE" "FCPI" "FCPIMT" "OPCVM"
Germany	"GENUSSCHEINE" ".GSH" " GSH" "%"
Greece	" PR " "PB" "PR." ".PR" ".PR"
Italy	"RNC" "RIGHTS" "PV" " RP "
Netherlands	"CERT" "CERTS"
New Zealand	"RTS"
Portugal	" R " "'R'"
Singapore	"NCPS" "NCPS100" "NRFD" "FB" "FBDEAD"
Sweden	"VXX" " USE " "CONVERTED" " CONV"
Switzerland	" USE " "CONVERTED" "CONV" "CONVERSION"
United Kingdom	"PAID" " NV " " NV."
Emerging Markets	
Brazil	" PN" "PNA" "PNB" "PNC" "PNC" "PNE" "PNF" "PNG" "RCSA" "RCTB" "PNDEAD" "PNADEAD" "PNBDEAD" "PNCDEAD" "PNDDEAD" "PNEDEAD" "PNFDEAD" "PNGDEAD"
Colombia	"PFCL" "PRIVILEGIADAS" "PRVLG"
India	"XNH"
Indonesia	"FB" "FBDEAD" " RTS" "RIGHTS" "RIGHTS"
Israel	"P1"
Malaysia	" A " "'A'" "FB" "(XCO)" "XCODEAD" " SES" "(SES)" "RIGHTS"
Mexico	"ACP" "BCP" " 'C'" " 'L'" " 'L'" " O " " 'O'" " C " " L "
Peru	"INVERSION" "INVN" " INV"
Philippines	"PDR"
South Africa	"'N'" "CPF" "OPTS" "OPTS"
South Korea	"1P" "2P" " 3P" "1PB" "1PB" "3PB" "4PB" "5PB" "6PB" "1PFD" "1PF" "PF2" "2PF"
Taiwan	"TDR" "'TDR'"
Thailand	"FB" "FBDEAD"

2.4 Risk factor and portfolio construction

This section describes the calculation of the right-hand side (RHS) risk factors (e.g., $RMRF$, SMB, HML, and WML) and of the portfolios whose returns should be explained on the left-hand side (LHS) of the regression framework (e.g., 5×5 sorts on size and book-to-market).

2.4.1 *RHS portfolios*

The Fama-French three-factor model consists of three RHS risk factors. These risk factors are the market excess return ($RMRF$), the size factor (SMB, small minus big), and the value factor (HML, high minus low). The Carhart four-factor model further incorporates a momentum factor (WML, winner minus losers).

The calculation of the market factor is straightforward. For one month, the market factor ($RMRF$) for a certain market is determined by the difference of the market return (RM) of a region and the risk-free rate (RF). The market return of a region is the value-weighted average of the returns of all stocks in my sample for a particular region.

The determination of the other RHS risk factors usually follows the methodology provided by Fama and French (1993) and Carhart (1997). Each year all stocks within a sample are sorted independently into two size groups, Big (B) and Small (S), and three book-to-market (B/M) groups, High (H), Medium (M), and Low (L). At the intersection of the two size (S and B) and three B/M groups (H, M, and L), six portfolios are constructed. The size factor, SMB, is the difference between the average monthly returns of the three small and the three big stock portfolios, whereas the value factor, HML, is the difference between the average monthly returns of the two high and two low B/M portfolios.

$$SMB_t = \frac{(r_t^{S/L} + r_t^{S/M} + r_t^{S/H}) - (r_t^{B/L} + r_t^{B/M} + r_t^{B/H})}{3}. \tag{1}$$

$$HML_t = \frac{(r_t^{S/H} + r_t^{B/H}) - (r_t^{S/L} + r_t^{B/L})}{2}. \tag{2}$$

Additionally, each month, all stocks are sorted by their cumulative past performance into three momentum groups, Winner (W), Neutral (N), and Loser (L). Based on the intersection of the two size and three momentum groups, six size-momentum portfolios are constructed. Similar to the calculation of the value factor, the momentum factor, WML, is the difference between the average monthly returns of the two winner and two loser portfolios.

$$WML_t = \frac{(r_t^{S/W} + r_t^{B/W}) - (r_t^{S/L} + r_t^{B/L})}{2}. \tag{3}$$

The three factors are zero-cost portfolios related to size, book-to-market, and past performance. By construction, they measure returns spreads of portfolios based on certain characteristics and should be neutral in regard to (the market and) the other factors.

2.4.2 *LHS portfolios*

Sorting stocks into portfolios on the basis of characteristics is common practice since the earliest tests of the CAPM (Fama and MacBeth, 1973; Black et al., 1972). Using portfolios instead of single securities has several advantages. First, portfolio returns are less noisy and variables, such as beta, can be estimated with higher accuracy. Second, portfolios are more stable than individual securities regarding the sorting characteristic, e.g., market capitalization or book-to-market ratio. Therefore, time-varying regression slopes should be a minor problem.

However, through grouping stocks into portfolios, there is also a loss of information. Berk (2000) highlights that through grouping stocks into portfolios, the within portfolio variation is lost. Therefore, stocks should be grouped into portfolios such that the cross-sectional variation in portfolio returns is large, but the within portfolio cross-sectional variation of stock returns is rather small.[30] This results in a trade-off for the researcher between portfolio diversification and less noise (smaller number of portfolios but a higher number of stocks per portfolio) and a high dispersion of portfolio returns (higher number of portfolios but a smaller number of stocks per portfolio).

Lewellen et al. (2010) propose industry portfolios as alternative test assets to avoid the models playing "home games" (Fama and French, 2012, p. 460). As Fama and French (2012) clarify, industry portfolios may have the problem of time-varying regression slopes, due to time-varying characteristics (beta, size, book-to-market). Furthermore, industry portfolios tend to have less variation in average returns.

For the number of LHS assets, different sorting schemes exist. For one-dimensional sorts in the U.S., typically decile portfolios are constructed (Jegadeesh and Titman, 1993, 2001; Lakonishok et al., 1994; Fama and French, 1996). This works also for larger markets outside the U.S., but for smaller markets only five portfolios are built to guarantee that the portfolios are well diversified (e.g., Rouwenhorst, 1998; Waszczuk, 2013).

For the two-dimensional sorting in the U.S., 5×5 sorts are standard (Fama and French, 1993, 2012; Griffin, 2002). This grouping into 25 portfolios is applied also for larger countries such as the U.K., Japan, or developed countries (Daniel et al., 2001; Griffin, 2002; Fama and French, 2012; Gregory et al., 2013). For smaller markets like Germany, 4×4 sorts offer a good trade-off between a sufficient split within

30 See Berk (2000) and Cochrane (2005).

each dimension and a good diversification (Schrimpf et al., 2007; Artmann et al., 2012; Hanauer et al., 2013). 5×5 sorts for smaller markets such as Hong Kong (Lam et al., 2010) or emerging markets regions (Cakici et al., 2013) with fewer securities compared to developed markets should be considered critical as sufficient portfolio diversification in this case is questionable. For dimensions that are correlated with each other or for young and small markets, researchers sometimes use 3×3 portfolios (e.g., Lakonishok et al., 1994; Fama and French, 1996; Waszczuk, 2013).

2.4.3 *Portfolio breakpoints*

While the construction of the market return is straightforward, different approaches exist for the determination of the other three RHS factors and the LHS assets. All methods are based on Fama and French (1993). Fama and French (1993) want to avoid a high weight of tiny stocks within the small size portfolios. Therefore, they use the median market capitalization of all NYSE stocks of a year to split NYSE, AMEX, and NASDAQ stocks into portfolios as NYSE stocks have, on average, a higher market capitalization. In contrast to CRSP, Datastream does not provide time-varying information about the listing of a stock. Thus, even for the U.S., the breakpoints cannot be calculated in the same way as with CRSP. In the literature three main approaches exist to handle this problem.

2.4.3.1 *Breakpoints by Griffin (2002)*

Griffin (2002) applies the same percentiles for the RHS and LHS portfolios as Fama and French (1993). However, he calculates the breakpoints on the whole sample of stocks in a region and not only on a subsample of bigger stocks (e.g., NYSE stocks for the U.S.). For the determination of RHS risk factors, Griffin (2002) splits the stocks of a region by the median into two size groups. For the RHS book-to-market splits, Griffin (2002) uses the 30^{th} and 70^{th} percentiles of all stocks as breakpoints. The LHS portfolios are, regarding the two dimensions size and value, formed by quintile breakpoints for the 5 groups per dimension. For 4×4 portfolios, the use of quartile breakpoints would be consistent with the approach of Griffin (2002).

As a result, sorting schemes for both RHS and LHS portfolios are dominated by tiny stocks within small size portfolios. To illustrate my results, I show the shares of aggregated market capitalization for the six size-value portfolios for an emerging markets sample in Table 5. The sample of common stocks is derived from the constituent lists of Table 2, and the screens described in Subsections 2.2.1 and 2.2.2 are applied. This sample of emerging market stocks is also used to calculate the value factor, HML, in Chapter 3.

If I would use the breakpoint approach suggested by Griffin (2002), the share of the aggregate market capitalization of the small size group (S) in relation to the total aggregate market is only 3%. Hence, 3 out of 6 portfolios are formed by stocks, which represent only 3% of the aggregated market capitalization in emerging markets.

2.4.3.2 *Breakpoints by Schmidt et al. (2010)*

To avoid the domination of the small group portfolios by tiny stocks, Schmidt et al. (2010) calculate the percentiles of the market capitalization from all stocks in the U.S. that correspond to the breakpoints based solely on NYSE stocks applied by Fama and French (1993). They conclude that the 80^{th} percentile of all stocks roughly corresponds to the median of the NYSE stocks and the 60^{th}, 70^{th}, 80^{th}, and 90^{th} percentiles correspond to the quintiles of the NYSE stocks. Therefore, they split the stocks by these percentiles of all stocks into different size groups. The value and momentum breakpoints are the 30^{th} and 70^{th} percentiles for the RHS portfolios and quintiles for LHS portfolios. For 4×4 sorts, I adapt the size breakpoints by Schmidt et al. (2010). By interpolating, I determine the following size breakpoints: 62^{nd}, 75^{th}, and 89^{th} percentiles. Consistent with Schmidt et al. (2010),

Table 5: **Share of aggregated market capitalization for different breakpoint approaches**
The table reports the average shares of aggregated market capitalization for the six size-value portfolios for an emerging markets sample. The sample of common stocks is derived from the constituent lists in Table 2, and the screens described in Subsections 2.2.1 and 2.2.2 are applied. This sample of emerging market stocks is also used to calculate the value factor, HML, in Chapter 3. The three applied breakpoint approaches are based on Griffin (2002), Schmidt et al. (2010) and Fama and French (2012). At the end of June of each year y, all stocks are sorted independently into two size groups, Big (B) and Small (S), and three B/M groups, High (H), Medium (M), and Low (L). At the intersection of the two size and three B/M groups, I construct six portfolios (S/H, S/M, S/L, B/H, B/M, and B/L). The statistics are computed over the period July 1996 to June 2012.

	L	M	H	**Sum**
Griffin (2002)				
S	0.01	0.01	0.01	0.03
B	0.48	0.41	0.07	0.97
Sum	0.49	0.43	0.09	
Schmidt et al. (2010)				
S	0.05	0.06	0.03	0.14
B	0.43	0.37	0.06	0.86
Sum	0.49	0.43	0.09	
Fama and French (2012)				
S	0.02	0.04	0.05	0.10
B	0.26	0.40	0.24	0.90
Sum	0.28	0.44	0.28	

the value and momentum breakpoints for four groups are quartiles on all stocks.

By applying the breakpoints by Schmidt et al. (2010), the share of the aggregate market capitalization of small stocks (S) in emerging markets is 14% (see Table 5). However, as for the breakpoint approach by Griffin (2002), stocks with higher market capitalization are dominating the low (L) and medium (M) book-to-market portfolios. Both approaches result in an aggregated market capitalization share of only 9% for the high book-to-market portfolios (H), although they represent 30% of all emerging market stocks.

2.4.3.3 *Breakpoints by Fama and French (2012)*

As I have mentioned before, the method by Fama and French (2012) is based on the method by Fama and French (1993) for the U.S. market.

Fama and French (2012) mention that the NYSE median corresponds roughly to 90% of the aggregate market capitalization. As they extend their analysis to an international setting, they calculate the size breakpoints that big stocks represent the top 90% of the aggregate market capitalization. For the size dimension of the portfolios with the 2×3 sorts (RHS factors), they classify stocks that are in the top 90% of the aggregate market capitalization of a region as big (B) and those in the bottom 10% as small (S) stocks. The value breakpoints are the 30th and 70th percentiles of the book-to-market ratio of the big stocks. Nevertheless, these breakpoints are also applied for small stocks. The same conventions are applied for the calculation of momentum groups.

For the 5×5 portfolio sorts, Fama and French (2012) use the 3rd, 7th, 13th, and 25th percentile of a region's aggregate market capitalization as breakpoints for size portfolios. Fama and French (2012) use quintile book-to-market and past performance breakpoints for the biggest stocks to allocate the stocks to their five value and momentum groups, respectively. I have to adapt their size and value breakpoints when calculating 4×4 sorts. By roughly interpolating their four size breakpoints, I attain three size breakpoints which are the 4th, 10th, and 20th percentiles of a region's aggregate market capitalization. For the four value and momentum groups, I determine quartile breakpoints on book-to-market and past performance for the group with the biggest stocks. Again, I use these breakpoints to allocate all the stocks into value and momentum groups. The calculation of breakpoints based solely on the biggest stocks should avoid an unbalanced distribution of the market capitalization in value and momentum groups.

Table 5 presents the share of aggregated market capitalization for the six size-value portfolios forming HML in emerging markets. Per definition, the share of aggregated market capitalization for small stock portfolios (S) is 10%. However, by calculating the book-to-market breakpoints solely on big stocks (B), the market capitalization is distributed more evenly over the book-to-market groups: both, low and high book-to-market stocks represent 28% of the aggregated market capitalization of all stocks.

In sum, the calculation steps and the principal approach of the three methods are similar. The main difference between the methods is the calculation of the size breakpoints. The goal of the method by Fama and French (2012) is to avoid sorts that are dominated by tiny stocks. Therefore, they use size breakpoints related to the aggregate market capitalization. Their breakpoints to determine the LHS assets for value and momentum are based on the group of the largest stocks. The methods by Griffin (2002) and Schmidt et al. (2010) use size breakpoints which are a proportion of the total number of stocks. Also, their value and momentum breakpoints are based on all stocks for LHS and RHS assets.

In Chapters 3 and 4, I follow the breakpoint approach by Fama and French (2012) as their approach seems to be the most balanced concerning the distribution of the aggregated market capitalization over the individual portfolios. However, I apply the other two breakpoint approaches in Chapter 5. As the calculation of the ICC is based on earnings forecasts from I/B/E/S and this subsample, similar to NYSE stocks, is biased toward larger stocks, I use the breakpoint approach of Griffin (2002) for this sample. For the analysis based on the full sample (also including smaller stocks not covered by I/B/E/S) within Chapter 5, I calculate breakpoints based on Schmidt et al. (2010).

2.5 COMPARABILITY OF RESULTING RISK FACTORS

This section presents the comparability of the risk factors resulting from the process described above with risk factors obtained from Kenneth French's data library.[31] Kenneth French's risk factors are applied in his studies with Eugene F. Fama (e.g., Fama and French, 1993, 2012), and are updated on a monthly basis. They are perceived as high-quality benchmark factors and are used in many other studies.[32]

2.5.1 *Risk factors for the U.S.*

First, I want to evaluate the comparability of my risk factors for the U.S. with counterparts constructed as in Fama and French (1993). These factors are also used in the analysis of my full sample in Chapter 5. Table 6 shows descriptive statistics for my risk factors and their counterparts for the same period, downloaded from Kenneth French's website.

Table 6: **Descriptive statistics for my risk factors and their counterparts for the U.S.**
The table reports means, standard deviations, and pairwise correlations for my risk factors and their counterparts for the same period, downloaded from Kenneth French's (KF's) website. My risk factors are also used in the analysis of my full sample in Chapter 5. The factors from KF data library are calculated as in Fama and French (1993). All returns are in USD. The statistics are computed over the period July 1990 to December 2011.

	RMRF	SMB	HML
Risk factors applied in Chapter 5			
Mean	0.53	0.17	0.32
Std dev.	[4.41]	[3.39]	[3.55]
Risk factors from KF's data library			
Mean	0.51	0.21	0.28
Std dev.	[4.50]	[3.47]	[3.29]
ρ	1.00	0.98	0.96

31 See mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
32 E.g., Asem and Tian (2010), Asness et al. (2013), or Daniel and Moskowitz (2013).

Despite the fact that the factors are based on different data providers, the resulting risk premiums are quite similar. On average, the value weighted excess returns of the market yield 0.51% and 0.53% per month, with an almost perfect correlation of 1.00 (rounded value). Although I calculate the size breakpoints as the 80% quantile over all stocks, and not as the median of all NYSE stocks as in Fama and French (1993), the size factors, SMB, are very close. The average monthly premiums in Kenneth French's and my datasets for the U.S. are 0.21% and 0.17%, respectively. The correlation coefficient between the two size factors is 0.98. A similar difference exists for the value factor, HML. My average value premium is 0.32% per month, while the premium provided by Kenneth French yields only 0.28%. Despite this deviation, their correlation coefficient of 0.96 is still very high. Figure 1 illustrates the aforementioned results and plots the cumulative performance of the risk factors from my as well as Kenneth French's dataset. Again, the high comparability between both datasets can be observed.

Altogether, I show that the sample selection, data screens, and choice of sample breakpoints described in this chapter lead to risk factors for the U.S. that are very close to the factors obtained from Kenneth French's website. This evidence documents that the resulting risk premiums are not specific for CRSP/Compustat data. Furthermore, my results suggests that the data screens are appropriate to ensure data quality for data provided by Thomson Reuters.

2.5.2 *Risk factors for international markets*

Second, I want to compare the risk factors applied in Chapters 3 and 4 with the international benchmark factors calculated as in Fama and French (2012). Again, these factors are obtained from Kenneth French's data library.

Figure 1: **Cumulative performance of my risk factors and their counterparts for the U.S.**
The figure plots the cumulated performance of the monthly time-series of the market (RMRF), the size factor (SMB), and the value factor (HML) for the U.S. "MH" denotes for my risk factors, whereas "KF" denotes for the risk factors downloaded from Kenneth French's data library. All returns are in USD. The statistics are computed over the period July 1990 to December 2011.

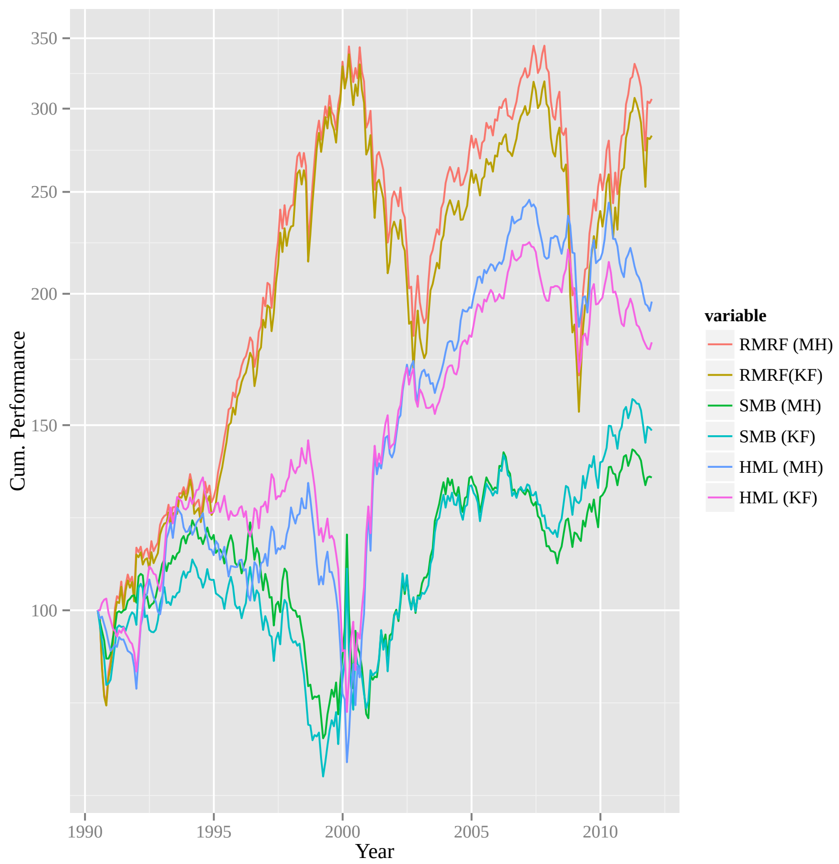


Table 7: **Descriptive statistics for my risk factors and their counterparts for Japan**
The table reports means, standard deviations, and pairwise correlations for my risk factors and their counterparts for the same period, downloaded from Kenneth French's (KF's) website. My risk factors are also used in the analysis of the Japanese market in Chapter 4. The factors from KF's data library are calculated as in Fama and French (2012). All returns are in USD. The statistics are computed over the period November 1990 to September 2012.

	RMRF	SMB	HML	WML
Risk factors applied in Chapter 4				
Mean	-0.10	-0.11	0.68	0.10
Std dev.	[5.75]	[3.47]	[2.39]	[4.70]
Risk factors from KF's data library				
Mean	-0.12	-0.05	0.44	0.10
Std dev.	[5.89]	[3.38]	[2.88]	[4.68]
ρ	0.99	0.97	0.86	0.98

Table 7 presents means, standard deviations, and pairwise correlations for my Japanese risk factors and those downloaded from Kenneth French's website for the overlapping period from November 1990 to September 2012.[33] As for the U.S. risk factors, the resulting risk premiums are quite similar. While the market and the momentum factors appear nearly identical, the size and value factors exhibit some deviations. The average premiums for the size factor, SMB, are -0.11% and -0.05% for my and Kenneth French's datasets, while the premiums for the value factor are 0.68% and 0.44%, respectively. I hypothesize that the different portfolio construction dates cause these deviations. As I describe in Subsection 4.3.2, my construction date is end of September for each year y and the book value is for the fiscal year end that falls between April of year $y-1$ and March of year y, while Fama and French (2012) use end of June as construction date and the book value is for the fiscal year ending in calendar year $y-1$ for all regions. As the majority of the companies listed in Japan have March 31 as their financial year end, I use more current

33 Most of the calculations in Chapter 4 are based on returns measured in JPY. However, I use returns calculated in USD for robustness tests in Subsection 4.6.1. While my period covers October 1986 to September 2012, the momentum factor, WML, from Kenneth French's website is available starting in November 1990.

book values.[34] The more current book-to-market ratios may explain the higher average return of my value factor, HML, compared to the one from Kenneth French's data library.[35] However, the analysis in Chapter 4 focuses on the momentum factor, *WML*, which exhibits the same return (0.10%) and a nearly perfect correlation (0.98) with the momentum factor from Kenneth French's website. Figure 2 plots the cumulative performance of Japanese risk factors from the both datasets and illustrates the aforementioned results.

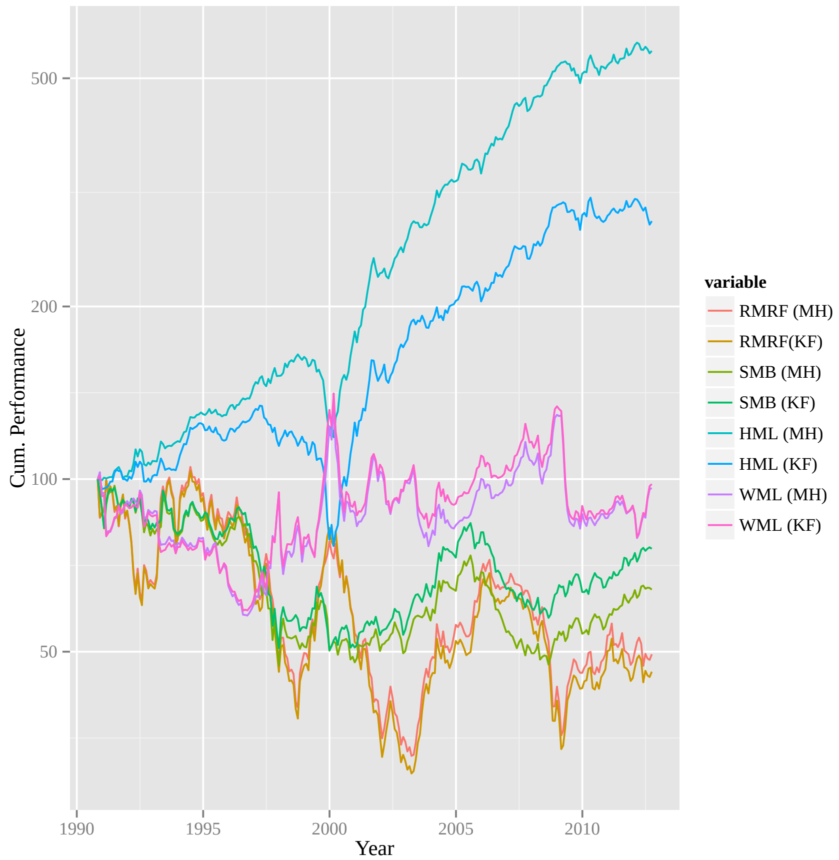
Table 8: **Descriptive statistics for my risk factors and their counterparts for global developed markets**
The table reports means, standard deviations, and pairwise correlations for my risk factors and their counterparts for the same period, downloaded from Kenneth French's (KF's) website. My risk factors are based on a subsample of my global risk factors in Chapter 3. The factors from KF's data library are calculated as in Fama and French (2012). All returns are in USD. The statistics are computed over the period July 1996 to June 2012.

	RMRF	SMB	HML	*WML*
Risk factors applied in Chapter 3				
Mean	0.35	-0.02	0.38	0.74
Std dev.	[4.73]	[2.24]	[2.97]	[5.01]
Risk factors from KF's data library				
Mean	0.34	0.02	0.44	0.66
Std dev.	[4.81]	[2.30]	[2.67]	[4.69]
ρ	1.00	0.99	0.91	0.95

In Chapter 3, I calculate risk factors for four emerging market regions and emerging markets as a whole, and global risk factors for both developed and emerging market countries. To the best of my knowledge, no downloadable risk factors for emerging markets exist. However, global developed market risk factors applied in Fama and French (2012) are available on Kenneth French's website. The residual returns between my global market returns and emerging market returns correspond to the returns of global developed markets. Therefore, I calculate risk factors solely based on developed market countries with the same methodology as for emerging markets to finally validate my risk factor calculation methodology. Table 8 documents

34 See also Chan et al. (1991) or Daniel et al. (2001).
35 See Asness and Frazzini (2013).

Figure 2: **Cumulative performance of my risk factors and their counterparts for Japan**
The figure plots the cumulated performance of the monthly time-series of the market (*RMRF*), the size factor (*SMB*), the value factor (*HML*), and the momentum factor (*WML*) for the U.S. "MH" denotes for my risk factors, whereas "KF" denotes for the risk factors downloaded from Kenneth French's data library. All returns are in USD. The statistics are computed over the period November 1990 to September 2012.

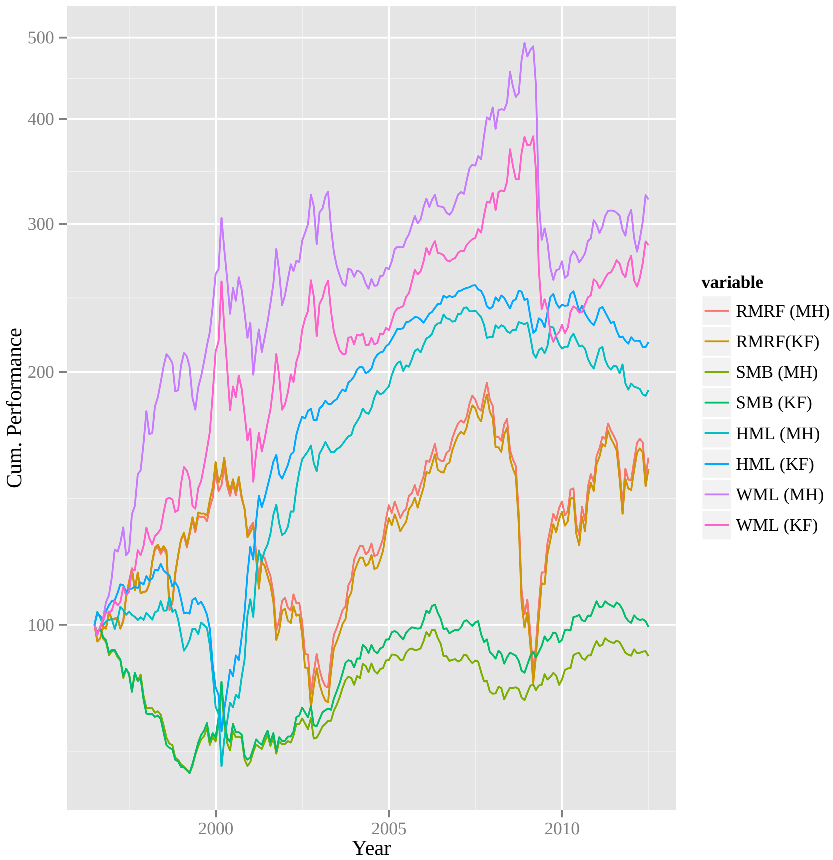


descriptive statistics for both my and Kenneth French's dataset. The risk premiums exhibit small deviations, potentially, as I do not calculate region-specific, but rather global value and momentum breakpoints. Fama and French (2012) motivate region-specific breakpoints to account for differences in accounting rules. However, these choice is arbitrary as accounting rules are country-specific. Furthermore, they use global size breakpoints. In my view, only country-specific or global breakpoints are consistent. Hence I use global breakpoints for size, value, and momentum portfolios.

Nonetheless, the pairwise correlations range from 1.00 (rounded value) for the market excess returns to 0.91 for the value factors; the means and standard deviation exhibit the same levels. As for U.S. and Japanese risk factors, Figure 3 plots the cumulative performance of the risk factors for global developed markets from both datasets. Despite the different value and momentum breakpoints, the factors exhibit a similar behavior over the observation period, with the biggest deviations for the returns of the momentum factors.

In sum, these results underline my detailed and thorough data process; data quality issues should not affect the results in subsequent chapters.

Figure 3: **Cumulative performance of my risk factors and their counterparts for global developed markets**
The figure plots the cumulated performance of the monthly time-series of the market (RMRF), the size factor (SMB), the value factor (HML), and the momentum factor (WML) for global developed markets]. "MH" denotes for my risk factors, whereas "KF" denotes for the risk factors downloaded from Kenneth French's data library. All returns are in USD. The statistics are computed over the period July 1996 to June 2012.



3

SIZE, VALUE, AND MOMENTUM IN EMERGING MARKET STOCK RETURNS: INTEGRATED OR SEGMENTED PRICING?

In this chapter, I examine size, value, and momentum patterns in the stock returns of four emerging market regions - Latin America, EMEA, Asia, and BRIC.[36] I document a strong and highly significant value effect, and a strong but less significant momentum effect. In contrast to developed markets, significant value and momentum premiums are also present for big stocks and the overall premiums are driven not only by small stocks. Furthermore, the value patterns in emerging markets are more pronounced than in developed markets. In order to examine integrated global pricing across these regions, I test whether empirical asset pricing models with global factors capture value and momentum patterns, and variation in average stock returns. Since global models perform poorly for emerging markets, I replace global risk factors by local risk factors. I gain strong support for the local four-factor model with market, size, value, and momentum factors. On the basis of my results, pricing in emerging markets does not seem to be globally integrated.

3.1 INTRODUCTION

Fama and French (2012) test whether empirical asset pricing models capture the value and momentum patterns in four developed regions (North America, Europe, Japan, and Asia Pacific), and whether asset pricing is integrated across these regions. They conclude that there is little evidence supporting integrated asset pricing across the four de-

36 This chapter is based on Hanauer and Linhart (2014).

veloped market regions and local models provide better results than the global models. While developed markets have been studied extensively in the past 35 years,[37] only few have investigated value and momentum effects in emerging markets, although the importance of emerging market economies and stock markets is constantly rising.[38]

Examining emerging market stock returns in this chapter is threefold. First, I determine the magnitude of standard risk factors on the basis of a broad sample of stocks from 21 emerging countries in a methodologically consistent way.[39] Second, I explore the size patterns in emerging market value and momentum returns. Third, I discuss market integration with a clear focus on emerging markets as a whole and four emerging market regions including the BRIC[40] region.

My analysis leads to three primary results. First, I find a strong and highly significant value effect, and a strong but less significant momentum effect in emerging markets. The size factor is less pronounced and is only significant in the emerging Asian markets and BRIC. Second, I provide evidence of value and momentum spreads for different size groups. I cannot document that value spreads are significantly smaller for big stocks than for small stocks in emerging markets as seen in Fama and French (2012) for developed markets. Furthermore, I get mixed results for momentum spreads. Third, I find little support for global integrated asset pricing in emerging markets as my global models fail to explain emerging market return variations. In contrast to the previous observation, local models with local risk factors fit well, and the local four-factor models, in particular, are

37 See, e.g., Basu (1977), Banz (1981), Rosenberg et al. (1985), Chan et al. (1991), Fama and French (1992), Fama and French (1993), or Griffin (2002).

38 The Organization for Economic Co-operation and Development (OECD) estimates a dramatic change in the relative size of economies within the next 50 years, a shift toward emerging countries (Johansson et al., 2012).

39 First studies of Fama and French (1998), Rouwenhorst (1999), Griffin et al. (2003), and van der Hart et al. (2003) show that value and momentum effects are also present in emerging markets. Despite these early studies, there only exist few single emerging country studies. E.g., Drew et al. (2003) analyze the Shanghai stock exchange and Waszczuk (2013) examines the Polish market.

40 The four emerging countries Brazil, Russia, India, and China (BRIC) are said to be the main drivers of rising economic importance (Wilson and Purushothaman, 2003).

appropriate asset pricing models to explain emerging market stock returns.

The papers closest to the analysis within this chapter are Griffin (2002), Fama and French (2012) and Cakici et al. (2013). Griffin (2002) compares world, international, and local three-factor models in order to explain excess returns in the U.S., Canada, the U.K., and Japan. His main finding is that the choice of the model is relevant and that the local models are more useful in explaining time-varying stock returns.

Fama and French (2012) analyze size, value, and momentum patterns in average stock returns for four regions comprising developed countries in a methodologically consistent way. Therefore, my findings complement their results by analyzing the relevant effects of emerging markets. They report value premiums in all regions that, except for Japan, decrease from smaller to bigger stocks. Significant momentum returns exist in all regions, except Japan. Again these premiums decrease with firm size. For the size factor, they document non-significant size premiums with different signs for the four regions. Moreover, they conduct performance tests of global and local versions of the CAPM, Fama-French three-factor, and Carhart four-factor asset pricing models. Based on their results, Fama and French (2012) conclude that there is little support for integrated asset pricing across the four developed market regions.

Cakici et al. (2013) conduct a similar emerging market study and report that local factors perform much better. Hence, they report that emerging markets are segmented. In contrast to Cakici et al. (2013), I remain more conservative regarding the observation period, number of portfolios, data selection, and the regional composition. This leads to three major differences. First, I find a positive momentum premium in Emerging Markets Eastern Europe. Second, and more importantly, I do not reject most of the local four-factor models as they do. Furthermore, as in Fama and French (2012) for developed markets, my models for emerging markets have more problems with size-momentum portfolios than with size-value portfolios, and not vice versa as seen in Cakici et al. (2013).

This chapter proceeds as follows. Section 3.2 describes the data preparation, selection of the regions, as well as portfolio and risk factor construction. Section 3.3 provides details about my applied models and performance test. Section 3.4 presents the descriptive statistics for my LHS assets and RHS factors. Sections 3.5 and 3.6 include asset pricing tests of global and local models for size-value and size-momentum portfolios, respectively. Section 3.7 presents asset pricing tests with a global emerging market model for regional portfolios. Section 3.8 concludes.

3.2 DATA, REGIONS, AND RISK FACTOR CONSTRUCTION

3.2.1 *Data*

My sample comprises data from 21 emerging countries and 24 developed countries over the July 1996 to June 2012 period. When choosing the observation period, I consider whether a longer observation period or a higher minimum amount of stocks per year resulting in higher diversification is more appropriate.

To derive my sample of international stocks, I use Thomson Reuters Datastream. I create a semi-automated and multilevel process to identify common stocks and secure data quality. During the first step, I identify stocks by Thomson Reuters Datastream's constituent lists.[41] Following Ince and Porter (2006), Griffin et al. (2010), and Schmidt et al. (2010), I apply static screens, the details of which are presented in Subsection 2.2.1. These screens ensure that my sample comprises exclusively of common stocks of each of the 45 countries.

This screening process results in a sample comprising 63,775 unique securities for developed countries and 21,612 unique securities for

41 I use Worldscope lists and research lists; moreover, to eliminate the survivorship bias I use dead lists.

emerging countries. I obtain return data from Datastream and accounting data from Worldscope. All items are measured in USD. As Ince and Porter (2006) describe, raw return data from Datastream may not be error-free. To ensure data quality, I follow Ince and Porter (2006) and Schmidt et al. (2010) and apply dynamic screens to the monthly return data, as described in Subsection 2.2.2.

To qualify for my sample from July of year y to June of year $y + 1$, a security needs a valid value for the market capitalization for June 30 of year y and December 31 of year $y - 1$, a positive book value at the fiscal year end of year $y - 1$ and valid stock returns for the last 12 months. I define book value as common equity plus deferred taxes, if available.

3.2.2 *Regions*

According to Morgan Stanley Capital International (MSCI), I classify the following countries as emerging market countries: Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Peru, Philippines, Poland, Russia, South Africa, South Korea, Taiwan, Thailand, and Turkey.[42]

Tables 9 to 11 show the number and the average market value (MV) in USD billion for stocks that meet my sample-selection criteria as of end of June of each year. Because the sample size of many emerging countries is too low to meet the demand of diversified portfolios on a country basis,[43] I construct, similar to Fama and French (2012), regional portfolios. This results in a greater diversification and more robust results.

42 In accordance with the MSCI classification, the following countries are labeled as developed market countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

43 For Russia, e.g., my sample contains 0 stocks in 1996, 1 stock in 1997, and 2 stocks in 1998.

Table 9: **Number and aggregated market value of stocks for EM Latin America**
The table shows the number and the aggregated market value (MV) in USD billion for stocks that meet my sample-selection criteria as of end of June of each year in EM Latin America (LatAm). To qualify for my sample from July of year y to June of year $y+1$, a security needs a valid value for the market capitalization for June 30 of year y and December 31 of year $y-1$, a positive book value at the fiscal year end of year $y-1$ and valid stock returns for the last 12 months.

	Brazil		**Colombia**		**Chile**		**Mexico**		**Peru**		**LatAm**	
	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV
1988												
1989							8	3			**8**	**3**
1990							13	7			**13**	**7**
1991					18	10	15	13			**33**	**23**
1992					26	20	18	17			**44**	**37**
1993			9	3	43	20	32	29	6	1	**90**	**52**
1994			16	9	55	51	36	41	17	2	**124**	**103**
1995			18	11	64	68	50	29	15	5	**147**	**113**
1996	26	16	20	9	73	49	52	40	16	7	**187**	**121**
1997	29	25	20	12	79	56	53	52	23	12	**204**	**157**
1998	31	22	22	7	90	42	64	52	22	8	**229**	**132**
1999	34	13	24	6	120	50	73	56	24	7	**275**	**131**
2000	52	17	24	3	167	55	85	62	26	6	**354**	**144**
2001	58	15	25	4	165	53	81	73	30	4	**359**	**149**
2002	55	11	26	5	161	43	78	53	31	5	**351**	**116**
2003	52	16	32	7	167	55	75	52	29	7	**355**	**137**
2004	48	23	34	12	165	79	75	67	32	10	**354**	**190**
2005	52	43	34	24	169	112	79	83	39	12	**373**	**275**
2006	58	97	33	30	172	123	79	104	61	19	**403**	**373**
2007	69	201	31	50	168	199	86	195	65	38	**419**	**683**
2008	105	272	32	44	170	185	83	214	76	43	**466**	**757**
2009	127	226	34	96	166	185	85	136	76	38	**488**	**681**
2010	128	349	37	134	166	230	80	188	78	52	**489**	**952**
2011	137	478	39	198	162	315	79	237	71	56	**488**	**1284**

Table 10: **Number and aggregated market value of stocks for EM EMEA**
The table shows the number and the aggregated market value (MV) in USD billion for stocks that meet my sample-selection criteria as of end of June of each year in EM EMEA (EMEA). To qualify for my sample from July of year y to June of year $y+1$, a security needs a valid value for the market capitalization for June 30 of year y and December 31 of year $y-1$, a positive book value at the fiscal year end of year $y-1$ and valid stock returns for the last 12 months.

	Czech R.		Hungary		Russia		Poland		Turkey		Egypt		Morocco		S. Africa		EMEA	
	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV
1988															47	37	**47**	**37**
1989															47	48	**47**	**48**
1990									5	3					54	64	**59**	**67**
1991									9	3					96	75	**105**	**79**
1992									11	4					102	95	**113**	**98**
1993									21	11					103	91	**124**	**102**
1994			6	1			5	1	42	10					119	117	**172**	**129**
1995			5	<1			7	2	46	20					129	122	**187**	**145**
1996	15	4	10	1			21	5	48	18					130	129	**224**	**157**
1997	52	11	19	6	1	<1	25	4	61	31					133	133	**291**	**185**
1998	60	12	22	7	2	<1	35	6	82	43	5	2	8	8	151	108	**365**	**187**
1999	58	12	29	12	3	8	51	12	101	39	14	4	8	7	252	129	**516**	**223**
2000	52	12	36	14	7	18	65	26	121	76	13	4	11	7	264	124	**569**	**281**
2001	49	8	36	9	10	23	77	22	135	38	19	6	16	7	223	123	**565**	**236**
2002	43	10	35	11	15	63	79	24	133	27	20	4	19	7	207	96	**551**	**243**
2003	38	13	34	13	16	95	88	28	160	37	29	5	21	10	197	112	**583**	**313**
2004	34	19	35	20	20	98	118	42	162	57	37	10	23	14	191	170	**620**	**429**
2005	35	30	35	31	26	143	135	55	180	99	44	36	22	14	190	218	**667**	**625**
2006	23	38	33	31	66	306	188	98	230	114	85	44	41	36	190	297	**856**	**964**
2007	22	52	35	49	96	754	209	194	219	200	94	81	50	55	195	403	**920**	**1788**
2008	18	78	37	41	130	1123	247	166	222	172	102	101	56	81	208	377	**1020**	**2139**
2009	13	40	36	21	159	444	270	84	150	146	105	58	69	67	193	296	**995**	**1156**
2010	14	39	38	24	156	632	295	109	212	233	101	59	71	63	192	360	**1079**	**1518**
2011	13	50	39	32	227	947	297	196	249	274	97	53	71	66	198	500	**1191**	**2119**

Table 11: **Number and aggregated market value of stocks for EM Asia**
The table shows the number and the aggregated market value (MV) in USD billion for stocks that meet my sample-selection criteria as of end of June of each year in EM Asia (Asia) and Emerging Markets (EM). To qualify for my sample from July of year y to June of year $y+1$, a security needs a valid value for the market capitalization for June 30 of year y and December 31 of year $y-1$, a positive book value at the fiscal year end of year $y-1$ and valid stock returns for the last 12 months.

	China		**India**		**Indon.**		**S. Korea**		**Malaysia**		**Philip.**		**Taiwan**		**Thailand**		**Asia**		**EM**	
	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV	#	MV
1988							19	13	37	11					2	<1	**58**	**24**	**105**	**61**
1989							50	35	46	15	2	1			7	2	**105**	**52**	**160**	**103**
1990							65	35	63	25	2	1	4	15	10	3	**144**	**79**	**216**	**153**
1991			4	2	4	1	73	42	70	30	3	1	3	12	15	5	**172**	**93**	**310**	**194**
1992	1	<1	21	6	54	9	87	38	118	48	14	8	10	17	61	17	**366**	**144**	**523**	**279**
1993	4	1	97	15	75	13	109	60	164	79	19	10	23	20	116	33	**607**	**231**	**821**	**385**
1994	16	3	160	51	80	20	171	107	200	135	25	20	45	66	180	68	**877**	**470**	**1173**	**703**
1995	31	9	175	46	92	30	218	133	218	162	48	28	107	98	218	108	**1107**	**615**	**1441**	**872**
1996	73	27	253	77	132	56	243	121	306	214	80	53	202	166	247	117	**1536**	**831**	**1947**	**1109**
1997	82	41	280	112	154	91	275	106	358	228	91	58	219	250	267	52	**1726**	**938**	**2221**	**1279**
1998	93	43	288	75	149	11	288	35	236	51	67	23	223	183	216	19	**1560**	**439**	**2154**	**758**
1999	100	56	298	95	126	34	363	165	181	77	57	35	228	236	236	53	**1589**	**752**	**2380**	**1106**
2000	203	150	312	138	167	30	553	196	380	117	75	30	352	311	229	34	**2271**	**1005**	**3194**	**1429**
2001	220	186	350	90	194	21	637	157	394	83	81	19	449	216	305	30	**2630**	**803**	**3554**	**1188**
2002	239	175	385	103	216	32	692	242	439	107	78	17	771	298	311	43	**3131**	**1017**	**4033**	**1377**
2003	1124	460	408	133	262	40	780	242	382	106	79	17	899	299	317	56	**4251**	**1353**	**5189**	**1804**
2004	1185	438	464	199	280	45	850	301	441	137	86	21	996	400	345	89	**4647**	**1631**	**5621**	**2251**
2005	1264	359	538	346	278	76	890	436	392	147	93	27	1103	489	360	100	**4918**	**1979**	**5958**	**2879**
2006	1282	528	628	527	295	93	1314	670	315	157	106	39	1181	537	399	118	**5520**	**2669**	**6779**	**4006**
2007	1269	1445	1681	911	300	159	1401	984	330	260	116	84	1223	735	428	155	**6748**	**4733**	**8087**	**7204**
2008	1372	1863	1874	939	315	182	1483	839	345	221	137	60	1261	674	428	162	**7215**	**4940**	**8701**	**7837**
2009	1498	2803	2030	946	340	149	1567	599	204	189	124	60	1333	535	375	127	**7471**	**5407**	**9854**	**7244**
2010	1504	2463	2073	1304	345	258	1599	762	271	268	138	89	1386	648	397	181	**7713**	**5973**	**9281**	**8443**
2011	1781	3533	2090	1411	348	380	1629	1108	310	375	152	143	1460	866	416	261	**8186**	**8078**	**9865**	**11481**

I combine the 21 emerging countries into three emerging market regions: EM Latin America,[44] including Brazil, Chile, Colombia, Mexico, and Peru; EM EMEA,[45] including Czech Republic, Hungary, Russia, Poland, Turkey, Egypt, Morocco, and South Africa; and EM Asia, including China, India, Indonesia, South Korea, Malaysia, Philippines, Taiwan, and Thailand. Because the average number of stocks in my emerging market regions is smaller when compared with those in developed markets, I split stocks of one region into 16 portfolios, and not 25 portfolios as in Fama and French (2012). Since each portfolio should be well diversified, I target an average of more than 10 stocks per portfolio and year, and hence, a minimum of at least 160 stocks per year in each region. Year 1996 is the first year that fulfills the condition of more than 160 stocks per region with 187 stocks in EM Latin America, 224 stocks in EM EMEA, and 1,536 stocks in EM Asia. Moreover, the aggregated market value of the regions (column MV indicates the aggregated market value of a country respective region) is considerably smaller before 1996. Hence, it is appropriate to begin the analysis in 1996. Also using data from Thomson Reuters Datastream, Cakici et al. (2013) construct 25 portfolios per year, beginning in January 1991. They use the same regional portfolios, except for EM EMEA, as they exclude Egypt, Morocco, and South Africa from this region and name it Eastern Europe.[46] However, if I followed their observation period and portfolio approach for my sample, then Eastern Europe would only include the following number of stocks per year in 1991 to 1995: 9, 11, 21, 53, and 58. Considering 25 portfolios, the fourth year for this approach would be the first year, when each portfolio includes more than one stock on average (as per my dataset). To meet the demand of diversified portfolios, I choose a more conservative method and aggregate Eastern European countries and three African countries to EM EMEA and begin my analysis in 1996.

44 I prefix "EM " for the emerging market regions to clearly indicate that they are not developed market regions.
45 EMEA denotes Europe, the Middle East, and Africa.
46 In EM Latin America, Cakici et al. (2013) include Argentina instead of Peru.

Market integration across the regions should be a reasonable assumption. The countries forming EM Latin America and EM Asia, respectively, are economically closely connected and mostly bordering countries. The economic connection is most questionable in EM EMEA with (East) European and African countries. I combine the countries of both continents as the number of stocks for each continent would be too small in the early years of my analysis to achieve diversified portfolios. Furthermore, also MSCI groups them as an emerging market region. BRIC, comprising Brazil, Russia, India, and China, is a forth additional emerging market region. It is reasonable to analyze BRIC as a whole, since these four countries are at a comparable stage of economic development (Wilson and Purushothaman, 2003). In addition, due to the demand of investors to collectively invest in these four markets, many investment vehicles such as ETFs have been issued for the BRIC markets as a whole.

Finally, I construct both the global sample and the Emerging Markets sample.[47] The global sample contains stocks from all 21 emerging countries, and 24 developed countries. This portfolio should capture all effects in a global context. The Emerging Markets sample contains stocks from the 21 emerging markets. Tests on the Emerging Markets sample are a good indicator of whether a hypothesis or model is valid across the whole emerging market universe.

3.2.3 *Risk factor and portfolio construction*

I construct the risk factors (RHS factors) and test portfolios (LHS assets) for the global (only RHS factors) and emerging market sample as well as for each region following an adapted version of the method in Fama and French (2012).[48] The four RHS factors are the market fac-

47 I denote the sample comprising all 21 emerging market countries as "Emerging Markets" (in capital letters).

48 I also conduct robustness tests on adapted versions of the methods applied by Griffin (2002) and Schmidt et al. (2010). The main results for these two alternative breakpoint methods are the same. However, some observations exhibit more noise due to the

tor (RMRF), the size factor (SMB, small minus big), the value factor (HML, high minus low), and the momentum factor (WML, winner minus losers).

RMRF is the excess return of the market return (RM), a value-weighted return of all stocks in a sample over the risk-free rate (RF). I use the one-month T-bill rate as a proxy for the risk-free rate.

At the end of June of each year y, I sort all stocks of a region independently into two size groups, Big (B) and Small (S), and three book-to-market (B/M) groups, High (H), Medium (M), and Low (L). According to Fama and French (2012), big stocks (B) represent the top 90% of the aggregate market capitalization at the end of June of year y, while small stocks (S) represent the bottom 10%.[49] B/M is calculated as the book value at the fiscal year end of year y divided by the market capitalization at the end of December of year $y-1$. The breakpoints for the book-to-market ratio are the 30th and 70th percentiles of B/M for the biggest stocks, but also applied to small stocks. For my global and Emerging Market sample I use the same approach as for the regions. In contrast, Fama and French (2012) allocate the stocks of their global portfolio on the basis of four regional breakpoints.

At the intersection of the two size and three B/M groups, I construct six portfolios (S/H, S/M, S/L, B/H, B/M, and B/L). Monthly value-weighted returns are calculated for the next twelve months starting from July of year y until June of year $y+1$. The portfolios are reformed at the end of June of year $y+1$.

Based on theses portfolios, I construct the monthly time-series of SMB and HML as follows:

$$SMB_t = \frac{(r_t^{S/L} + r_t^{S/M} + r_t^{S/H}) - (r_t^{B/L} + r_t^{B/M} + r_t^{B/H})}{3}. \tag{4}$$

less balanced distribution of the aggregated market capitalization over the individual portfolios.

49 Fama and French (1993) calculate the median for all NYSE stocks, but apply this breakpoint to all NYSE, AMEX, and NASDAQ stocks. They want to avoid a high weight of tiny stocks within the size dimension as NYSE stocks have on average a higher market capitalization. Fama and French (2012) mention that the NYSE median corresponds roughly to 90% of the aggregate market capitalization.

$$HML_t = \frac{(r_t^{S/H} + r_t^{B/H}) - (r_t^{S/L} + r_t^{B/L})}{2}. \tag{5}$$

To construct the momentum factor WML, for each month t, I sort stocks by their cumulative performance from month $t-11$ to month $t-1$. Again, the momentum breakpoints for all stocks are the 30th and 70th percentiles of lagged performance for the biggest stocks (B). L denotes losers (bottom 30% of lagged return), N denotes neutral (middle 40%), and W denotes winners (top 30%). The intersection of the size and momentum sorts results in six portfolios S/L, S/N, S/W, B/L, B/N, and B/W and the calculation of the momentum factor, WML, is similar to that of the value factor, HML:

$$WML_t = \frac{(r_t^{S/W} + r_t^{B/W}) - (r_t^{S/L} + r_t^{B/L})}{2}. \tag{6}$$

The determination of the RHS risk factors is similar to the methods adopted in Fama and French (2012). However, I adjust the methods for the generation of the LHS assets, since I allocate stocks to 4×4 portfolios and not to 5×5 portfolios. These 4×4 portfolios serve as LHS assets for my regressions and offer adequate possibilities for interpretation due to a sufficient split within each dimension and good diversification.[50]

By roughly interpolating the four size breakpoints in Fama and French (2012), I attain three size breakpoints which are the 4th, 10th, and 20th percentiles of a region's aggregate market capitalization. Fama and French (2012) use quintile value breakpoints for big stocks to allocate the stocks to their five value groups. Since I have four value groups, I use quartile value breakpoints on book-to-market ratios for the group with the biggest stocks. Again, I use these breakpoints derived from the biggest size group for all stocks to allocate

50 See Subsection 2.4.2 for more detailed information.

them to value groups. The intersection of these four size groups and four value groups forms the 4×4 LHS assets for my asset pricing tests (size-value portfolios) at the end of June of each year y. Monthly value-weighted returns are calculated for all portfolios for the next twelve months starting from July of year y until June of year $y+1$. The portfolios are reformed at the end of June of year $y+1$. To allocate stocks to the four momentum groups, for each month t, I use quartile momentum breakpoints for the biggest stocks to allocate all stocks. The intersection of the four size groups and four momentum groups forms my second 4×4 LHS assets for asset pricing tests (size-momentum portfolios). Again, monthly value-weighted returns are calculated.

3.3 METHODOLOGY

To explain the returns of the LHS assets, I use three factor models - the CAPM, Fama-French three-factor model, and Carhart four-factor model:

CAPM:

$$R_{it} - RF_t = a_i + b_i RMRFt + e_{it}. \tag{7}$$

Fama-French three-factor model:

$$R_{it} - RF_t = a_i + b_i RMRFt + s_i SMB_t + h_i HML_t + e_{it}. \tag{8}$$

Carhart four-factor model:

$$R_{it} - RF_t = a_i + b_i RMRFt + s_i SMB_t + h_i HML_t + w_i WML_t + e_{it}. \tag{9}$$

$R_{it} - RF_t$ is the excess return of portfolio i over the risk-free rate RF for month t. $RMRF$, SMB, HML, and WML denote the risk factors described above and are the respective returns of the factor-mimicking portfolios. They are either constructed from the global or the local samples. The three global models out of global factors are applied on the Emerging Market sample and all single regions. The local models are separately constructed for each region out of local factors. R_{it} can be either the return of a portfolio from sorts on size and value or from sorts on size and momentum.

Applying a global or local model on a sample implies the application of a regression on each of the 16 portfolios of a sample (set of regressions). If one particular model (local or global) is an appropriate asset pricing model for a sample, then the slopes of the model's risk factors (RHS factors) should explain the average returns of each of the 16 portfolios. Therefore, the regression intercepts should jointly be statistically indistinguishable from zero. To test this hypothesis, I use the F-test of Gibbons et al. (1989, hereafter GRS) and the related p-value. The GRS test statistic indicates whether the applied model is an appropriate estimator for the returns of the 16 portfolios from a statistical perspective.

As Fama and French (2012) highlight, power is often a problem in these tests. For local models power is sometimes too high, while that for global models, it is sometimes too low. The higher the explanatory power (R^2) of the regression, the better the regression fits. This leads to rejections of a model although the average absolute intercepts are rather low, and vice versa. Therefore, I present the average adjusted R^2 and the average absolute intercept for a set of regressions to evaluate a model from an economic perspective. The average absolute intercept for a set of regressions indicates whether the average portfolio returns are explained by the risk factors, while the average adjusted R^2 describes whether the variation in returns for each portfolio is captured by the model.

Furthermore, I provide the average standard error of the intercepts $s(a)$ and the core of the GRS statistic $SR(a)$:

$$SR(a) = (a'S^{-1}a)^{1/2}, \tag{10}$$

where a is the vector of intercepts and S as covariance matrix of regression residuals. According to Gibbons et al. (1989) and Fama and French (2012), $SR(a)$ is the maximum Sharpe ratio that can be constructed from the RHS factors and LHS assets minus the maximum Sharpe ratio that can be constructed from the RHS factors alone.

Similar to Griffin (2002) or Fama and French (2012), I use returns in USD for the tests of international asset pricing. This would be a problem if purchasing power parity does not hold or the assets I analyze are exposed to exchange rate risk. For example, see Solnik (1983) and Adler and Dumas (1983) for a theoretical background and Zhang (2006) for an empirical implementation of a model that allows exchange rate risk.

3.4 Descriptive Statistics

This section provides the summary statistics of the RHS explanatory returns - $RMRF$, SMB, HML, and WML - followed by the summary statistics of the 16 size-value and 16 size-momentum portfolios that serve as LHS assets in the analysis presented in Sections 3.5 and 3.6.

3.4.1 *Explanatory returns*

Table 12 presents summary statistics for the risk factors $RMRF$, SMB, HML, and WML in the global and Emerging Markets sample and the four emerging market regions. Over the July 1996 to June 2012 period, the average risk-free rate is 0.23% for all regions.

The average market return and average excess market return of the global portfolio are 0.60% and 0.37%, respectively. The global excess market return is slightly lower than the excess return for Emerging Markets of 0.40%. Notably, the excess market returns of these two samples are not significant. Fama and French (2012) determine a market excess return of 0.44% for their global portfolio comprising only developed markets (1991-2010).[51] EM Latin America has the highest excess return of 1.01% and is the only emerging market region with a significant market excess return. The other three emerging market regions including BRIC have insignificant equity premiums between 0.26% and 0.81%.

The size factor is small and insignificant in the global portfolio, which is highly dominated by developed markets. This result is in line with Fama and French (2012). For the Emerging Market portfolio, the SMB premium is 0.25%, however insignificant. The BRIC region has

51 The residual returns between my global market returns and Emerging Market returns corresponds to the returns of global developed markets. In Subsection 2.5, I compare my risk factors for global developed markets with the returns published on Kenneth's French website that are calculated as in Fama and French (2012). I obtain similar levels for the risk factor premiums and pairwise correlations ranging from 1.00 for the market excess returns to 0.91 for the value factors. This should underline my detailed and thorough data process.

the highest SMB return with a value of 0.62% followed by EM Asia with a mean of 0.41%, both significant at the 10% level. EM Latin America and EM EMEA have insignificant and smaller size factor mean returns.

In contrast, the value factor is high and significant for Emerging Markets (mean of 0.93% and a t-statistic of 3.04) and is nearly as twice as high as for the global portfolio with a value of 0.47%. Again, BRIC is the region with the highest HML mean of 1.20%. Each of the four emerging market regions have significant value factors, confirming the strong significance of the value factor in the Emerging Market portfolio. With the exception of EM EMEA, the value premiums are larger for small stocks; however, besides EM Latin America, the difference is not significant. Furthermore, the magnitude and significance of the value premium for big stocks in Emerging Markets and emerging market regions are higher than those for the global or developed markets (Fama and French, 2012).

The momentum factor, WML, has the highest mean return for BRIC (1.07%), followed by Emerging Markets (0.97%), EM Asia (0.94%), and the global portfolio with 0.88%. For the global and Emerging Markets sample, WML is significant at the 5% level and has the highest magnitude of the three factors. This is also stated for developed markets by Fama and French (2012). Contrary to the global and Emerging Markets sample, the momentum factor is not statistically significant in EM Latin America and EM EMEA. In EM Asia and BRIC, the WML mean is the highest within the region, significant at the 10% level. The momentum premiums for small and big stocks are statistically indistinguishable for Emerging Markets and all emerging market regions, with the exception of BRIC. For the global sample, I report higher momentum returns for small stocks compared with big stocks, however, the difference is less significant as in Fama and French (2012).

Analyzing EM Eastern Europe instead of EM EMEA would result in risk premiums of 0.89%, -0.49%, 0.94%, and 0.51% for RMRF, SMB, HML, and WML, respectively, with the same significance levels as in EM EMEA. Thus, in contrast to Cakici et al. (2013), I document a positive momentum premium EM Eastern Europe. As mentioned in Section 3.2, the low number of stocks in the early years of their study (not included in my analysis) could be the reason for this difference.

In sum, the excess market return is only significant for EM Latin America and the size factor is only significant at the 10% level for BRIC and EM Asia. The value factor is significant in the global and Emerging Markets sample as well as in all emerging market regions. The momentum factor is also positive for all samples, however, despite the high magnitude, the momentum factor is not as significant as the value factor. Moreover, in the BRIC region SMB, HML, and WML returns have the highest means compared to other regions. In contrast to global and developed markets, significant value and momentum premiums are present for big stocks, and the overall premiums are not only driven by small stocks.

Table 13 presents the correlations between market, size, value, and momentum factors in the same region, while Table 14 shows the correlations between the same factors in different regions. In each of the six regions, the size and value factors are negatively correlated. For developed markets, Asness et al. (2013) report that value and momentum are negatively correlated. For the regions analyzed in this chapter, I can only confirm this result for the global portfolio and EM Latin America.[52] Nevertheless, I can confirm the consistent negative correlation of market and momentum factor, which is reported by Cakici et al. (2013), for all regions except BRIC. A potential explanation for this result might be that momentum returns tend to be negative when the market rebounds after a period of poor performance.[53]

For market, size, value, or momentum strategies across regions, the correlations of the factors between different regions might be interesting. The mean correlation of the four factors - market, size, value, and

52 Asness et al. (2013) use the market capitalization of the most recent month to compute the B/M ratio. They highlight that the correlation between value and momentum becomes more negative than using lagged market capitalization as I do.

53 See Asem and Tian (2010) and Hanauer (2014) for further information.

momentum - in Table 14 are 78%, 26%, 31%, and 47%, respectively. The low factor correlations might offer multiregional diversification potentials for size, value, or momentum strategies, but they also indicate potential market segmentation.

3.4.2 *Excess returns for the 16 size-value and 16 size-momentum portfolios*

Between 1963 and 1991, Fama and French (1993) find a negative relationship between size and average returns, and a strong positive relationship between average returns and book-to-market equity in the U.S. Nevertheless, they report low returns for small growth stocks. This finding is confirmed by Fama and French (2012) for North America, Europe, and Asia Pacific, but not for Japan (1991 to 2010). Besides Japan, Fama and French (2012) report a standard size effect for extreme value stocks and a reverse size effect for extreme growth stocks.

The left half of Table 15 presents the descriptive statistics for the 16 size-value portfolios. I document a size effect - rising portfolio returns from the bottom to the top for a value group - for all value portfolios of Emerging Markets. The same applies for most of the value portfolios of EM Asia and BRIC, and the two growth portfolios of EM EMEA. In contrast to Fama and French (2012), the reverse size effect for growth stocks does not exist in emerging market samples, with the exception of EM Latin America.

My sample displays the typical value premium - rising portfolio returns from the left to the right of a size group. The value-growth spread - excess return of the value minus excess return of the growth portfolio for a specific size group - is highly positive for all size groups. The value premium is larger for the smallest stocks than for the biggest stocks in EM Latin America and BRIC, smaller in EM EMEA, and about the same in EM Asia and Emerging Markets. An explanation for this deviation from developed markets is that the reverse size effect for growth stocks is not present in my samples except

EM Latin America. Furthermore, the value patterns for big stocks are more pronounced in emerging market samples compared with developed markets in Fama and French (2012).

Besides Japan, Fama and French (2012) report a momentum premium in all size groups and a size premium in the two momentum groups with the past year winners for all regions. The right half of Table 15 shows the results for the average excess market returns of the 16 size-momentum portfolios.

I find a size effect for all momentum groups - decreasing returns from the top to the bottom for the second to the forth column - for Emerging Markets. This finding confirms the results of Fama and French (2012) regarding their global portfolio. Size patterns in the single regions exist in most of the momentum groups but contain some more outliers compared with Emerging Markets.

The momentum effect is present within all size groups in all samples, although the effect is not very strong for the biggest stocks in EM Latin America. With one exception, the momentum premium is highly consistent for Emerging Markets - the equity premiums in each line continuously increase from left to right. I find smaller momentum spreads for the biggest stocks than for the smallest stocks in EM Latin America and BRIC but also higher spreads in Emerging Markets, EM EMEA, and EM Asia. This underlines the mixed results for WML in Table 12.

In sum, I document size, value, and momentum pattern in emerging market size-value and size-momentum sorted portfolios, however, I cannot provide clear evidence suggesting that value and momentum patterns decrease with size as for developed markets.

Table 12: **Descriptive statistic for risk factors in emerging markets**
The table reports summary statistics of the market return (RM), the excess return of the market over the risk-free rate ($RMRF = RM - RF$), the size factor (SMB), the value factor (HML), and the momentum factor (WML) for the global sample, Emerging Markets, and the emerging market regions EM Latin America, EM EMEA, and EM Asia. At the end of June of each year y, I sort all stocks of a region independently into two size groups, Big (B) and Small (S), and three B/M groups, High (H), Medium (M), and Low (L). According to Fama and French (2012), big stocks (B) represent the top 90% of the aggregate market capitalization at the end of June of year y, while small stocks (S) represent the bottom 10%. B/M is calculated as the book value at the fiscal year end of year y divided by the market capitalization at the end of December of year $y-1$. The breakpoints for the book-to-market ratio are the 30[th] and 70[th] percentiles of B/M for the biggest stocks, but also applied to small stocks. At the intersection of the two size and three B/M groups, I construct six portfolios (S/H, S/M, S/L, B/H, B/M, and B/L). Monthly value-weighted returns are calculated for the next twelve months starting from July of year y until June of year $y+1$. The portfolios are reformed at the end of June of year $y+1$. I construct value-growth returns for big and small stocks $HML_B = B/H - B/L$ and $HML_S = S/H - S/L$, and HML is the difference between HML_B and HML_S. To construct the momentum factor WML, for each month t, I sort stocks by their cumulative performance from month $t-11$ to month $t-1$. Again, the momentum breakpoints for all stocks are the 30[th] and 70[th] percentiles of lagged performance for the biggest stocks (B). L denotes losers (bottom 30% of lagged return), N denotes neutral (middle 40%), and W denotes winners (top 30%). The intersection of the size and momentum sorts results in six portfolios S/L, S/N, S/W, B/L, B/N, and B/W. I construct winner-looser returns for big and small stocks $WML_B = B/W - B/L$ and $WML_S = S/W - S/L$, and WML is the difference between WML_B and WML_S. All returns are in USD. The statistics are computed over the period July 1996 to June 2012.

	RM	RMRF	SMB	HML	HML_S	HML_B	HML_{S-B}	WML	WML_S	WML_B	WML_{S-B}
Global											
Mean	0.60	0.37	0.03	0.47	0.74	0.21	0.53	0.88	1.07	0.69	0.38
Std dev	4.81	4.82	2.35	3.11	4.04	2.80	3.11	5.13	4.88	5.91	3.50
t-Mean	1.74	1.07	0.19	2.10	2.52	1.03	2.35	2.38	3.04	1.62	1.50
Emerging Markets											
Mean	0.63	0.40	0.25	0.93	1.05	0.80	0.25	0.97	0.99	0.96	0.03
Std dev	6.71	6.72	2.70	4.23	5.27	3.92	3.84	6.84	8.02	6.73	5.63
t-Mean	1.30	0.82	1.28	3.04	2.76	2.85	0.89	1.97	1.71	1.98	0.07
EM Latin America											
Mean	1.24	1.01	-0.11	0.55	0.61	0.49	0.12	0.41	0.51	0.32	0.19
Std dev	6.65	6.67	3.15	3.33	3.71	4.39	4.66	4.74	5.72	5.62	6.20
t-Mean	2.58	2.09	-0.47	2.30	2.30	1.55	0.37	1.20	1.23	0.78	0.42
EM EMEA											
Mean	1.04	0.81	0.05	1.10	1.04	1.16	-0.12	0.67	0.61	0.73	-0.12
Std dev	8.05	8.06	3.68	4.77	5.73	5.53	5.99	6.72	6.62	8.00	5.90
t-Mean	1.80	1.40	0.19	3.21	2.52	2.92	-0.28	1.38	1.27	1.26	-0.29
EM Asia											
Mean	0.49	0.26	0.41	0.79	0.91	0.66	0.25	0.94	0.93	0.95	-0.02
Std dev	7.06	7.07	3.06	5.15	6.08	5.17	4.61	7.76	9.04	7.72	6.48
t-Mean	0.97	0.51	1.88	2.11	2.08	1.77	0.76	1.68	1.43	1.71	-0.04
BRIC											
Mean	0.89	0.65	0.62	1.20	1.58	0.82	0.77	1.07	1.47	0.67	0.80
Std dev	6.84	6.83	4.54	6.13	7.35	6.76	7.02	8.24	9.54	8.18	6.65
t-Mean	1.80	1.33	1.90	2.71	2.98	1.67	1.51	1.79	2.13	1.13	1.67

Table 13: **Correlations between market, size, value, and momentum factors in the same region**
The table presents the correlations between market, size, value, and momentum factors in the same sample. The samples are the global (Global) and Emerging Markets (EM) sample, and the emerging market regions EM Latin America (EM LatAm), EM EMEA, EM Asia, and BRIC. Details for the construction of the factors are provided in Table 12. The statistics are computed over the period July 1996 to June 2012.

	RMRF	SMB	HML	RMRF	SMB	HML
	Global			**EM**		
RMRF	1.00			1.00		
SMB	-0.03	1.00		-0.09	1.00	
HML	-0.15	-0.27	1.00	0.14	-0.15	1.00
WML	-0.21	0.09	-0.15	-0.16	-0.20	0.08
	EM LatAm			**EM EMEA**		
RMRF	1.00			1.00		
SMB	-0.57	1.00		-0.34	1.00	
HML	0.05	-0.05	1.00	-0.09	-0.28	1.00
WML	-0.24	0.13	-0.04	-0.14	0.13	0.26
	EM Asia			**BRIC**		
RMRF	1.00			1.00		
SMB	0.03	1.00		0.03	1.00	
HML	0.12	-0.13	1.00	0.10	-0.15	1.00
WML	-0.22	-0.20	0.05	0.06	-0.06	0.16

Table 14: **Correlations between the same risk factors for different regions**
The table reports the correlations between the same risk factors in different regions. The samples are the global (Global) and Emerging Markets (EM) sample, and the emerging market regions EM Latin America (LatAm), EM EMEA, EM Asia, and BRIC. The four RHS factors are RMRF, SMB, HML, and WML. Details for the construction of the factors are provided in Table 12. The statistics are computed over the period July 1996 to June 2012.

	Global	EM	LatAm	EMEA	EM Asia	Global	EM	LatAm	EM EMEA	EM Asia
	RMRF					SMB				
Global	1.00					1.00				
EM	0.83	1.00				0.34	1.00			
LatAm	0.82	0.85	1.00			-0.04	0.23	1.00		
EM EMEA	0.81	0.82	0.81	1.00		0.02	0.19	0.29	1.00	
EM Asia	0.74	0.97	0.75	0.68	1.00	0.31	0.91	0.05	-0.06	1.00
BRIC	0.65	0.82	0.67	0.65	0.81	0.19	0.64	0.17	0.03	0.60
	HML					WML				
Global	1.00					1.00				
EM	0.56	1.00				0.66	1.00			
LatAm	0.18	0.13	1.00			0.53	0.41	1.00		
EM EMEA	0.33	0.27	-0.02	1.00		0.52	0.42	0.31	1.00	
EM Asia	0.44	0.94	0.07	0.04	1.00	0.58	0.95	0.32	0.26	1.00
BRIC	0.43	0.56	0.14	0.11	0.52	0.44	0.58	0.26	0.25	0.56

Table 15: **Descriptive statistics for size-value and size-momentum portfolios in emerging markets**
The table reports summary statistics for the 16 size-value and 16 size-momentum sorted portfolios in Emerging Markets (EM) and the emerging market regions EM Latin America (EM LatAm), EM EMEA, and EM Asia. At the end of June of each year y, I attain three size breakpoints which are the 4^{th}, 10^{th}, and 20^{th} percentiles of a region's aggregate market capitalization. I use quartile value breakpoints on book-to-market ratios for the group with the biggest stocks. Again, I use these breakpoints derived from the biggest size group for all stocks to allocate them to value groups. The intersection of these four size groups and four value groups form the 4×4 LHS assets for the asset pricing tests (size-value portfolios). Monthly value-weighted returns are calculated for all portfolios for the next twelve months starting from July of year y until June of year $y+1$. The portfolios are reformed at the end of June of year $y+1$. To allocate stocks to the four momentum groups, for each month t, I use quartile momentum breakpoints for the biggest stocks to allocate all stocks. The intersection of the four size groups and four momentum groups form the second 4×4 LHS assets for asset pricing tests (size-momentum portfolios). Again, monthly value-weighted returns are calculated. All returns are in USD. The statistics are computed over the period July 1996 to June 2012.

	Size-value portfolios								Size-momentum portfolios							
	Mean				Standard deviation				Mean				Standard deviation			
	Low	2	3	High	Low	2	3	High	Low	2	3	High	Low	2	3	High
EM																
Small	0.44	0.85	0.59	1.32	7.90	7.45	7.09	7.97	0.74	1.07	1.62	1.26	10.62	7.01	6.71	7.44
2	-0.11	0.33	0.59	1.11	7.47	7.19	7.13	7.74	0.00	0.62	1.13	1.36	9.86	7.12	6.56	7.66
3	-0.09	0.16	0.47	0.85	6.94	6.91	6.87	7.45	-0.23	0.22	0.78	1.09	9.22	6.66	6.14	7.48
Big	-0.05	0.22	0.43	0.85	6.93	6.89	6.97	7.33	-0.07	0.25	0.27	0.70	9.02	6.87	6.67	7.70
EM LatAm																
Small	0.22	1.28	1.05	1.45	6.39	6.42	5.72	6.01	1.11	1.14	1.76	1.69	7.43	5.85	6.12	5.89
2	0.65	1.29	1.00	0.93	7.04	9.68	6.88	6.50	0.76	0.67	1.27	1.22	8.12	7.03	6.28	6.83
3	0.66	0.67	1.11	1.17	8.87	6.50	7.14	6.56	0.74	0.92	1.24	1.36	8.60	6.73	6.52	7.12
Big	0.66	1.08	1.19	1.30	7.56	7.01	7.08	8.19	1.00	0.80	1.27	1.09	9.12	7.30	6.84	7.77
EM EMEA																
Small	0.67	0.82	0.90	1.41	9.09	9.54	9.10	7.04	0.69	1.31	1.39	1.30	9.03	7.96	7.36	8.26
2	0.24	0.55	0.90	1.34	9.88	8.26	8.58	7.65	0.62	0.52	0.62	1.72	9.85	7.38	7.57	9.28
3	0.21	0.72	0.97	0.84	9.32	7.91	8.39	8.11	0.25	0.54	0.67	0.81	9.53	7.72	7.56	8.99
Big	0.10	0.71	0.96	1.54	9.34	8.60	8.63	8.84	0.68	0.58	0.49	1.33	10.53	9.09	8.82	9.16
EM Asia																
Small	0.51	0.54	0.35	1.22	8.94	8.28	7.81	9.00	0.65	0.77	1.25	1.08	11.95	8.23	7.63	8.36
2	0.12	0.70	0.45	1.15	8.37	8.21	8.07	8.57	0.09	0.46	1.17	1.45	10.65	8.42	7.59	8.36
3	0.15	0.20	0.28	0.79	7.44	7.83	7.63	8.37	-0.24	0.03	0.60	1.08	10.33	7.88	6.75	8.05
Big	-0.07	0.05	0.18	0.58	7.35	7.42	7.16	8.07	-0.16	-0.21	0.16	0.70	10.44	7.47	6.78	8.10
BRIC																
Small	1.08	0.93	1.25	2.07	9.33	9.40	8.96	9.64	0.89	1.70	2.03	2.43	10.46	9.28	9.31	10.27
2	0.22	0.88	0.87	2.33	8.99	8.88	9.22	9.35	0.67	1.09	1.51	2.42	10.09	8.73	8.60	9.96
3	0.40	-0.04	0.75	1.42	7.77	9.53	8.23	9.25	0.19	0.53	0.81	1.48	9.49	8.12	8.62	9.03
Big	0.56	-0.06	0.33	1.13	7.58	7.07	7.39	8.24	0.34	0.37	0.18	1.00	8.73	7.36	7.16	8.90

3.5 ASSET PRICING TESTS FOR SIZE-VALUE PORTFOLIOS

I primarily analyze market integration of emerging markets, and extend the results of Fama and French (2012) to these emerging markets. In this section, I regress global and local risk factors on excess returns of portfolios from 4×4 sorts on size and value. Table 16 presents the summary results. For each region, I present the following regression statistics for the CAPM, Fama-French three-factor model, and Carhart four-factor model: The GRS statistic of Gibbons et al. (1989), respective p-value p, average absolute intercept $|a|$, average adjusted R^2, average standard error of the intercepts $s(a)$, and the core of the GRS statistics $SR(a)$. The intercepts for the tests of selected models and regions are shown in Table 17.

The ideal asset pricing model for a region should have a small GRS statistic with a high corresponding p-value. The p-value represents the confidence level for the rejection of the hypothesis that the intercepts of a regression set are jointly zero. The average absolute intercept $|a|$, the average standard error of the intercepts $s(a)$, and the Sharpe Ratio for the intercepts $SR(a)$ should be small. However, it is also important for an appropriate asset pricing model that the model explains the variation in returns as much as possible. An indicator of a good explanatory power is a high adjusted R^2.

I present the regression results for Emerging Markets in Subsection 3.5.1, while Subsection 3.5.2 shows the results for the emerging market regions.

3.5.1 *Global and local models for Emerging Market size-value portfolio returns*

The global CAPM and the local CAPM have GRS statistics at approximately 1.30; thus, these models cannot be reject . I observe a high average absolute intercept $|a|$ of more than 0.30 for both models and a low R^2 (51%) for the global model. The explanatory power for the local model is higher with 80%. Thus, the local CAPM explains more variation in returns and performs better. However, the average absolute intercept is still high with a value of 0.33. Table 17 documents the remaining value and size patterns in the intercepts of the local CAPM.

For the three-factor model, the GRS statistic of the local model is 0.85 compared with 1.02 for the global model, thus, I cannot reject both models. The explanatory power of the local model is 92% compared with 66% for the global model; the average absolute intercept sharply drops to 0.09 for the local model compared to 0.20 for the global model. Among all the regressions of local and global models on portfolios of different regions, the average absolute intercept $|a|$ of the local model for Emerging Markets has the smallest value, and the GRS statistic is one of the best values. Consequently, the local three-factor model does a reasonable job in explaining excess returns of Emerging Market portfolios. For the global model, the missing (explanatory) power is the problem. The global model only explains two-thirds of the excess returns variation, and not sufficiently explaining the variation in stock returns. In economic terms, the global model fails although it is not rejected by the GRS test. Table 17 shows no remaining value or size pattern in the intercepts of the local three-factor model.

There is only a marginal improvement in Emerging Markets by adding the momentum factor. For the global model, the GRS statistic decreases by 0.05 to 0.97 and the R^2 increases by 1% to 67%. For both, global and local models, the average absolute intercepts increase by 0.03 and $s(a)$ and $SR(a)$ remain unchanged, respectively. The GRS statistic for the local four-factor model falls to 0.83, while the explanatory power remains at 92%. There are negligible changes in the intercepts by adding WML to the regressions. Using the four-factor model instead of the three-factor model only adds little value for size-value portfolios. As global models fail due to the low power, I do not find support for global market integration of Emerging Markets.

Fama and French (2012) demonstrate that excluding microstocks helps the models to survive the GRS statistics as they have problems explaining the wider value spreads for the smallest stocks. When regressing global risk factors on portfolios from 3×4 sorts, the GRS statistics on the right-hand side of Table 16 improve for all three global models, but the explanatory powers remain nearly unchanged. The tests of the local model on 3×4 portfolios result in better GRS statistics, and nearly unchanged explanatory powers. As the multifactor models in Emerging Markets do not leave patterns in the intercepts of the small stocks as in developed markets, the asset pricing tests in Emerging Markets do not improve much when microcaps are excluded. A potential reason is that the value-growth spreads of the portfolios show little variation among the four size groups of the Emerging Market portfolios (Table 15).

In sum, the global models fail to explain the returns of Emerging Market size-value portfolios. Although they pass the GRS test, missing (explanatory) power and higher average absolute intercepts are the problems. Instead, the local three-factor model is a good asset pricing model for Emerging Market size-value portfolios. Adding WML is not necessary but does not harm the results. In contrast to developed markets, microcaps do not seem to be a problem for Emerging Market size-value portfolios.

3.5.2 *Global and local models for regional emerging market size-value portfolio returns*

To analyze the four emerging markets regions in detail, I examine the statistics listed in Table 16. The global CAPM for EM Latin America, EM EMEA, and BRIC, and the three-factor model for EM Latin America and BRIC are the global models that are rejected at the 90% level. I cannot reject the other global CAPM, three-factor, or four-factor pricing models due to their GRS statistics. For the three global models in EM Asia, I determine marginally differing GRS statistics around 1.20. The average absolute intercepts for EM Asia range between 0.22 and 0.27, but the global models have low explanatory power with a maximum of 56% for the four-factor model, which is the highest value among all R^2 for regressions of global factors on excess returns of emerging market regions. The global models in Latin America and BRIC exhibit high average absolute intercepts (0.54 and 0.58 for the global four-factor model) which are approximately twice as high as the $|a|$ of the global models in Emerging Markets. The explanatory power is low with a maximum of 49% and 36% for the four-factor models. The average absolute intercepts and explanatory powers for the global models in EM EMEA are in-between the corresponding values for EM Asia and EM Latin America. Adding the momentum factor improves the GRS statistic for all models but does not improve the models from an economic perspective. Thus, the global models do poorly for emerging market regions due to power and intercepts, although the four-factor models, in particular, pass the GRS statistic.

In contrast, the local models are better suited for emerging market regions. The GRS statistics for the three models in EM Latin America are 1.46, 1.31, and 1.22. With those values, none of the models are rejected. This is an improvement, as the global CAPM and the global three-factor model for EM Latin America are rejected at the 10% significance level. Moreover, the absolute alphas are not even half the values of the respective global model, and especially the average absolute intercepts for the three-factor and four-factor models are within an acceptable range at 0.24 and 0.21, respectively. The explanatory power R^2 is 67% for the CAPM, 75% for the three-factor model, and 76% for the four-factor model. The intercepts for the local four-factor model in EM Latin America are listed in Table 17. The four-factor model has some problems with the smallest stocks which may be partly explained by the reverse size effect of growth stocks in this region (see Table 15).

In EM EMEA, the local CAPM must be rejected at the 99% level and a GRS statistics of 2.15. This rejection level is higher than the rejection level for the global CAPM, although the average alpha and standard error are lower and the R^2 is 72%, and thus 13% higher than for the global model. A reason for the weak GRS statistics of the local CAPM is the very pronounced value pattern in all four size groups in EM EMEA (see Table 15), which are not captured by the CAPM. The three-factor model is doing a good job explaining the returns and reaches a GRS statistic of 1.20; therefore, the three-factor model cannot be rejected. Moreover, there is no value pattern in the intercepts of the three-factor model (not reported) as it is able to capture that effect by the value factor. The R^2 jumps to 85% and the average absolute intercept $|a|$ is 0.19 with an average standard error of 0.25. Adding WML results in nearly identical summary statistics. Also, the intercepts from four-factor pricing (Table 17) are nearly unchanged compared with those of the three-factor pricing. Therefore, EM EMEA local multifactor models are doing better than the global multifactor models, as each single statistic is superior, especially the R^2 of 85% vs. 53% for the three-factor and four-factor models.[54]

For EM Asia, we can observe low GRS statistics and simultaneously high explanatory powers. The local three-factor and four-factor models have better GRS statistics compared to the global models for EM Asia returns, and neither of them is rejected. The R^2 of 76% of the local CAPM is substantially higher than the corresponding R^2 of the global CAPM, while the average absolute intercept of the local CAPM is 0.30. This value drops by nearly two-thirds to 0.11 when adding SMB and HML to the CAPM (three-factor model). The average standard error of the intercepts also drops to 0.19 and the R^2 jumps to

54 The GRS statistic of the global four-factor model is marginally lower; however, both global and local four-factor models cannot be rejected. Moreover, this discrepancy is outbalanced by the higher R^2 and the lower average absolute intercept of the local model.

89%, which is the best value for all the regressions in the three emerging market regions. The GRS statistic is 0.71 which results in a p-value of 0.78, and is only surpassed by the GRS statistic of 0.68 for the local four-factor model in EM Asia, with a p-value of 0.81. Aside from a minimal increase of $|\alpha|$ to 0.12, this is the only change when adding WML. The explanatory power R^2 for the four-factor pricing is also 89%, and the intercepts in Table 17 show no common pattern.

As observed for the other regions, the local three-factor and four-factor models dominate the global models for BRIC in explaining returns. In contrast to the local CAPM, the local three-factor and four-factor models are not rejected, the average absolute intercepts are only 0.26 and 0.23, and their explanatory power of 81% and 82% is acceptable. The intercepts in Table 17 do not exhibit size or value patterns; however, six out of eight intercepts of the extreme growth and extreme value portfolios are positive and the remaining intercepts of the portfolios with moderate book-to-market ratios (portfolios of value groups 2 and 3) are negative.

As the intercepts of microcaps do not exhibit exceptionally high values or patterns, I do not expect that excluding microcaps from my analysis add a lot of value. Although the GRS statistic improves for some global models, they still fail from an economic perspective. We can notice a considerable improvement for the local model in EM Latin America - the region that shows an inverse size effect for growth stocks and a more pronounced value pattern for the smallest stocks (Table 15). Besides EM Latin America, microcaps do not seem to cause problems for asset pricing models in emerging market samples as they do in developed markets. Thus, I conclude that local three-factor and four-factor models are reasonable asset pricing models for size-value portfolios in emerging market regions.

Table 16: **Summary statistics for regressions from sorts on size and value in emerging markets**
The table presents the summary statistics for regressions on portfolios from sorts on size and value, with (4×4) and without (3×4) microcaps for the following regions: Emerging Markets (EM), EM Latin America (EM LatAm), EM EMEA, EM Asia, and BRIC. The regressions use local or global versions of the CAPM (7), three-factor model (8), and four-factor model (9) with global or local factors. The GRS statistic tests whether all intercepts for a set of 16 (4×4) or 12 (3×4) regressions are jointly zero; p denotes the respective p-statistic for the GRS statistic; $|a|$ is the average absolute intercept for a set of regressions; R^2 is the average adjusted R^2; $s(a)$ is the average standard error of the intercepts; and $SR(a)$ is the Sharpe Ratio for the intercepts. All returns are in USD. The statistics are computed over the period July 1996 to June 2012.

	GLOBAL MODEL									**LOCAL MODEL**								
	4×4						3×4			4×4						3×4		
	GRS	p	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	GRS	p	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2
EM																		
CAPM	1.27	0.22	0.32	0.51	0.37	0.34	1.09	0.29	0.52	1.30	0.20	0.33	0.80	0.23	0.34	1.23	0.30	0.82
Three-factor	1.02	0.43	0.20	0.66	0.31	0.31	0.66	0.19	0.67	0.85	0.62	0.09	0.92	0.15	0.29	0.52	0.07	0.92
Four-factor	0.97	0.49	0.23	0.67	0.31	0.31	0.69	0.17	0.67	0.83	0.66	0.12	0.92	0.15	0.29	0.52	0.10	0.93
EM LatAm																		
CAPM	1.70	0.05	0.63	0.45	0.38	0.39	1.13	0.58	0.47	1.46	0.12	0.31	0.67	0.29	0.37	0.77	0.23	0.70
Three-factor	1.60	0.07	0.53	0.49	0.37	0.39	1.02	0.48	0.51	1.31	0.19	0.24	0.75	0.25	0.35	0.73	0.19	0.78
Four-factor	1.37	0.16	0.54	0.49	0.38	0.37	0.79	0.50	0.51	1.22	0.26	0.21	0.76	0.25	0.34	0.59	0.16	0.78
EM EMEA																		
CAPM	1.72	0.05	0.46	0.49	0.45	0.40	1.46	0.44	0.50	2.15	0.01	0.33	0.72	0.33	0.44	1.71	0.35	0.74
Three-factor	1.38	0.16	0.32	0.53	0.44	0.36	1.09	0.28	0.54	1.20	0.27	0.19	0.85	0.25	0.34	1.22	0.16	0.85
Four-factor	1.13	0.33	0.27	0.53	0.45	0.33	0.88	0.22	0.54	1.19	0.28	0.19	0.85	0.25	0.34	1.22	0.17	0.85
EM Asia																		
CAPM	1.22	0.26	0.27	0.39	0.45	0.33	1.41	0.26	0.39	1.25	0.24	0.30	0.76	0.28	0.34	1.45	0.27	0.78
Three-factor	1.24	0.24	0.22	0.55	0.39	0.34	1.20	0.23	0.56	0.71	0.78	0.11	0.89	0.19	0.26	0.74	0.10	0.90
Four-factor	1.19	0.28	0.24	0.56	0.40	0.34	1.19	0.20	0.56	0.68	0.81	0.12	0.89	0.19	0.26	0.72	0.12	0.90
BRIC																		
CAPM	1.69	0.05	0.67	0.20	0.56	0.39	2.20	0.55	0.21	1.73	0.04	0.52	0.61	0.39	0.40	2.20	0.47	0.64
Three-factor	1.62	0.07	0.62	0.36	0.51	0.39	2.12	0.52	0.37	1.12	0.34	0.26	0.81	0.28	0.33	1.39	0.29	0.81
Four-factor	1.50	0.10	0.58	0.36	0.52	0.38	1.85	0.47	0.37	1.07	0.39	0.23	0.82	0.27	0.32	1.34	0.26	0.82

Table 17: **Intercepts from CAPM, three-factor model, and four-factor model regressions from sorts on size and value in emerging markets**
The table presents the summary statistics for regressions on portfolios from sorts on size and value for the following regions: Emerging Markets, EM Latin America, EM EMEA, EM Asia, and BRIC. The regressions use local versions of the CAPM (7), three-factor model (8), and four-factor model (9) with local factors. For selected regions and models, the table reports intercepts, a, and t-statistics, $t(a)$, for the intercepts. All returns are in USD. The statistics are computed over the July 1996 to June 2012 period.

	a				$t(a)$			
	Low	2	3	High	Low	2	3	High
Emerging Markets: Local CAPM								
Small	0.06	0.46	0.21	0.91	0.17	1.74	0.94	3.17
2	-0.47	-0.04	0.21	0.70	-1.49	-0.13	0.93	2.78
3	-0.42	-0.20	0.09	0.44	-1.40	-0.93	0.47	2.06
Big	-0.44	-0.18	0.03	0.44	-2.85	-1.44	0.22	2.61
Emerging Markets: Local three-factor model								
Small	0.06	0.26	-0.16	0.10	0.28	1.48	-1.02	0.60
2	-0.21	0.02	-0.02	-0.06	-1.31	0.11	-0.13	-0.57
3	-0.11	-0.04	-0.02	-0.12	-0.54	-0.24	-0.12	-0.81
Big	-0.07	0.05	0.00	0.06	-0.67	0.52	-0.03	0.54
Emerging Markets: Local four-factor model								
Small	0.09	0.26	-0.12	0.21	0.40	1.46	-0.75	1.36
2	-0.16	-0.06	-0.12	-0.09	-0.97	-0.37	-0.81	-0.86
3	-0.16	-0.13	-0.15	-0.14	-0.78	-0.75	-0.88	-0.97
Big	-0.06	0.09	-0.02	0.08	-0.51	0.85	-0.18	0.71
EM Latin America: Local four-factor model								
Small	-0.36	0.57	0.28	0.28	-1.29	1.56	1.40	1.81
2	-0.07	0.19	-0.11	-0.26	-0.23	0.39	-0.44	-1.63
3	-0.29	-0.06	0.18	0.11	-0.79	-0.22	0.71	0.46
Big	-0.11	0.17	0.17	-0.19	-0.86	0.93	0.91	-1.20
EM EMEA: Local four-factor model								
Small	0.22	0.37	0.14	0.24	0.74	1.32	0.50	1.58
2	0.13	-0.19	-0.30	0.03	0.57	-0.75	-1.14	0.12
3	0.05	-0.16	-0.24	-0.46	0.16	-0.57	-0.83	-1.73
Big	0.15	-0.03	0.04	0.28	0.72	-0.12	0.19	1.44
EM Asia: Local four-factor model								
Small	-0.02	-0.07	-0.28	0.22	-0.06	-0.32	-1.44	1.12
2	-0.18	0.21	-0.25	0.02	-0.79	1.12	-1.33	0.17
3	0.08	-0.09	-0.23	-0.12	0.30	-0.39	-1.01	-0.64
Big	0.03	0.10	-0.04	-0.07	0.20	0.84	-0.25	-0.45
BRIC: Local four-factor model								
Small	0.39	-0.04	-0.01	0.17	1.17	-0.16	-0.05	0.54
2	-0.23	-0.09	-0.14	0.35	-1.02	-0.30	-0.48	1.64
3	0.08	-0.79	-0.14	-0.32	0.30	-1.63	-0.42	-1.11
Big	0.47	-0.35	-0.09	0.05	2.39	-1.58	-0.43	0.26

3.6 ASSET PRICING TESTS FOR SIZE-MOMENTUM PORTFOLIOS

This section presents my results for the regressions on portfolios from sorts on size and momentum. Similar to the table structure of the regressions on the size-value portfolios, Table 18 presents the summary statistics of the regressions on emerging market portfolio returns, and Table 19 documents the regression intercepts for the 16 portfolios of the most relevant model-sample combinations.

3.6.1 *Global and local models for Emerging Market size-momentum portfolio returns*

The global CAPM, global three-factor model, and global four-factor model are rejected by the GRS statistic at the 99% level for Emerging Markets. The results when applying the models on the size-value portfolios are different, and none of the models are rejected. This shows that the models are doing a better job in capturing the value effect than the momentum effect. I also find relatively high average absolute intercepts ranging from 0.54 for the CAPM to 0.36 for the four-factor model. The (unreported) intercept matrices show strong momentum patterns in the intercepts for each size group for the global CAPM and three-factor model, and a mild reverse momentum pattern for the megacaps of the global four-factor model. With values of 48%, 61%, and 65%, the R^2 of the three models are up to 5% smaller than the R^2 for the size-value portfolios. For the 3×4 Emerging Market portfolios, the global three-factor model is rejected at the 90% level, while the global four-factor model is rejected at the 95% level. Also, the explanatory powers do not increase significantly. As for the size-value portfolios, the global models explain Emerging Market size-momentum excess returns poorly, and I find no support for global market integration of Emerging Markets.

As previously stated, the local models perform well in the explanation of Emerging Market size-value portfolio returns. For the tests on size-momentum portfolio returns, the three local models have GRS statistics of 2.90, 2.59, and 2.29, implying that I reject the three models at the 99% level. The R^2 is 75% for the local CAPM, 81% for the local three-factor model, and 90% for the local four-factor model. Among the tests of global and local models on size-momentum portfolios, the R^2 is higher for the local models; however, all models are strictly rejected. The explanatory power of the local models for the size-momentum portfolios is smaller than those for the size-value portfolios. For the four-factor model, however, the difference is only 2%. The average absolute intercepts are also higher compared to the tests on size-value portfolios. Table 19 shows strong momentum patterns in the intercepts for the CAPM and the three-factor model. The small portfolio with the second highest past year performance has the highest intercept because the models are unable to explain the abnormally high return of this portfolio. When adding WML, these patterns vanish; however, high positive intercepts for three of the four microcaps portfolios remain. I expect that dropping microcaps results in an improvement of the model fit. Excluding microcaps (see Table 18) and considering the twelve portfolios from 3×4 sorts on size and momentum primarily improves the GRS statistic for local models. For the regressions of the local risk factors on Emerging Market excess returns, the GRS statistic for the three-factor and four-factor models drop to 1.41 and 1.01 and these models do not have to be rejected. This result confirms my expectation of a noticeable improvement for the 3×4 portfolio formation. Furthermore, because the R^2 is high at 91%, I conclude that the local four-factor model is doing well in pricing Emerging Market size-momentum portfolio returns, if microcaps are excluded. However, based on the statistics of the global models for the 3×4 portfolio sorts, I gain no support for global integrated pricing for Emerging Markets.

3.6.2 *Global and local models for regional emerging market size-momentum portfolio returns*

This subsection evaluates the effectiveness of global and local models on regional portfolios. In contrast to EM EMEA and EM Asia, I reject all global models for EM Latin America and global multifactor models for BRIC (see Table 18) due to GRS statistics. The models for EM Latin America and BRIC produce high average absolute alphas up to 0.83 and low average explanatory powers between 20% and 48%. The GRS statistics of the three global models for EM EMEA and EM Asia are significantly lower. Nevertheless, even the four-factor models have low explanatory powers (55%) and leave high average absolute intercepts of 0.34 and 0.32 for EM EMEA and EM Asia, respectively. In sum, the global four-factor models of EM EMEA and EM Asia produce similar statistics, especially GRS statistics, but suffer from low explanatory powers. In economic terms, the global four factors explain regional emerging market returns insufficiently. The models for EM Latin America fail due to the GRS statistics and the low R^2. As already suggested by the size-value portfolios and the Emerging Market size-momentum portfolios, integrated global pricing does not seem to be a valid assumption for the emerging market regions.

For EM Latin America, all local models are rejected at the 95% level, although the R^2 increases to values ranging between 66% and 77%, and the average absolute intercepts simultaneously fall compared to the global models. Compared to the results for the size-value portfolios, the GRS statistics, in particular, are worse and the average absolute intercepts are higher for the size-momentum portfolios.

The explanatory power for the three local models in EM EMEA is acceptable and ranges between 70% and 84%. Although the GRS statistics for the global three-factor and four-factor model are lower, they are not rejected. In EM Asia and BRIC, both the GRS statistics and R^2 are better for the local three-factor and four-factor models; thus, I cannot reject both local models. Among all tests on size-momentum portfolios, the GRS statistic of 0.85 for local four-factor pricing in EM Asia and BRIC are the lowest values. The average absolute intercepts for four-factor pricing in EM Latin America, EM EMEA, EM Asia, and BRIC are 0.26, 0.31, 0.18, and 0.24, respectively, which are the lowest values within each region.

Table 19 presents the intercept matrices for the regressions of the local four-factor models on the regional emerging market size-momentum portfolio returns. In the intercepts of the four-factor model in EM Latin America, I find a momentum pattern for microcaps and a milder reverse momentum pattern for megacaps. The winner-loser spread in mean returns of Table 15 for microcaps is 0.58 (1.69 - 1.11), and therefore approximately six times as large as the winner-loser spread for megacaps of 0.09 (1.09 - 1.00). However, the spreads in the four-factor WML-slopes (unreported) are 0.87 and 1.09 for small and large stocks, and the four-factor model does poorly in explaining the returns. The intercept matrices of EM EMEA and EM Asia do not show such patterns.

Thus, I expect the largest improvement in the statistics for EM Latin America using 3×4 sorts instead of 4×4 sorts for emerging market regions. Table 18 confirms my expectation, and neither any global nor local model is rejected for EM Latin America. The local four-factor model in EM Latin America has the lowest GRS statistic (0.81) among all tests of global and local models on 3×4 portfolio sorts. Compared to the tests on 4×4 portfolios, the explanatory power of the local and global models in EM EMEA and EM Asia either marginally improves or remains constant. The GRS statistics for the models in EM EMEA marginally decrease, while those in EM Asia marginally increase. As for the BRIC size-value portfolios, the tests on 3×4 portfolio sorts result in worse GRS statistics for the global models and marginally higher explanatory powers compared to the tests on 4×4 portfolios. Deleting microcaps in BRIC enhances the GRS statistic of the local four-factor model on size-momentum portfolios to 0.66, and the R^2

slightly increases to 81%. For EM Latin America, deleting microcaps is reasonable and the local four-factor model, in particular, seems to be a good asset pricing model if microcaps are excluded.

In sum, the local four-factor models are good pricing models in EM EMEA and EM Asia, in particular. With regard to the explanatory power, the local models are better than global models. In EM Latin America, the explanatory power increases substantially by substituting global with local risk factors; however, global and local models fail because of the high GRS statistics when microcaps are included. Independent of global or local models, the size-momentum portfolio formation generally produces worse statistics than the size-value portfolio formation. The difference is not that considerable in the explanatory power but in the GRS statistic.

Table 18: **Summary statistics for regressions from sorts on size and momentum in emerging markets**
The table presents the summary statistics for regressions on portfolios from sorts on size and momentum, with (4×4) and without (3×4) microcaps for the following regions: Emerging Markets (EM), EM Latin America (EM LatAm), EM EMEA, EM Asia, and BRIC. The regressions use local or global versions of the CAPM (7), three-factor model (8), and four-factor model (9) with global or local factors. The GRS statistic tests whether all intercepts for a set of 16 (4×4) or 12 (3×4) regressions are jointly zero; p denotes the respective p-statistic for the GRS statistic; $|a|$ is the average absolute intercept for a set of regressions; R^2 is the average adjusted R^2; $s(a)$ is the average standard error of the intercepts; and $SR(a)$ is the Sharpe Ratio for the intercepts. All returns are in USD. The statistics are computed over the period July 1996 to June 2012.

	GLOBAL MODEL									LOCAL MODEL								
	4 × 4						3 × 4			4 × 4						3 × 4		
	GRS	p	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	GRS	p	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2
EM																		
CAPM	2.78	0.00	0.54	0.48	0.40	0.50	1.99	0.47	0.48	2.90	0.00	0.54	0.75	0.28	0.51	1.97	0.46	0.77
Three-factor	2.46	0.00	0.47	0.61	0.36	0.48	1.75	0.45	0.61	2.59	0.00	0.44	0.81	0.25	0.50	1.41	0.41	0.82
Four-factor	2.22	0.01	0.36	0.65	0.34	0.47	1.83	0.24	0.66	2.29	0.00	0.20	0.90	0.18	0.48	1.01	0.15	0.91
EM LatAm																		
CAPM	2.06	0.01	0.76	0.43	0.38	0.43	1.50	0.64	0.46	1.97	0.02	0.40	0.66	0.29	0.43	1.25	0.30	0.69
Three-factor	1.94	0.02	0.63	0.47	0.38	0.43	1.37	0.51	0.49	2.02	0.01	0.36	0.72	0.27	0.44	1.07	0.31	0.73
Four-factor	1.53	0.09	0.68	0.48	0.38	0.39	1.02	0.56	0.51	1.87	0.03	0.26	0.77	0.24	0.43	0.81	0.19	0.79
EM EMEA																		
CAPM	1.10	0.36	0.42	0.49	0.44	0.32	1.06	0.31	0.50	1.08	0.38	0.35	0.70	0.34	0.31	1.00	0.29	0.72
Three-factor	1.29	0.21	0.36	0.53	0.43	0.35	1.18	0.28	0.54	1.44	0.13	0.33	0.77	0.31	0.38	1.31	0.33	0.77
Four-factor	1.14	0.32	0.34	0.55	0.44	0.34	0.97	0.26	0.56	1.44	0.13	0.31	0.84	0.25	0.38	1.30	0.31	0.84
EM Asia																		
CAPM	1.41	0.14	0.51	0.37	0.49	0.36	1.66	0.51	0.36	1.54	0.09	0.54	0.72	0.33	0.37	1.79	0.50	0.74
Three-factor	1.28	0.21	0.46	0.50	0.45	0.35	1.55	0.51	0.50	1.06	0.40	0.47	0.78	0.30	0.32	1.20	0.51	0.79
Four-factor	1.01	0.45	0.32	0.55	0.44	0.32	1.21	0.28	0.55	0.85	0.63	0.18	0.87	0.23	0.29	0.94	0.17	0.88
BRIC																		
CAPM	1.46	0.12	0.83	0.20	0.58	0.36	1.62	0.63	0.21	1.42	0.14	0.64	0.58	0.42	0.36	1.52	0.49	0.61
Three-factor	1.63	0.07	0.77	0.32	0.55	0.39	1.92	0.60	0.34	0.97	0.50	0.40	0.68	0.38	0.31	0.80	0.37	0.69
Four-factor	1.53	0.09	0.72	0.34	0.55	0.39	1.78	0.53	0.36	0.85	0.63	0.24	0.80	0.29	0.29	0.66	0.18	0.81

Table 19: **Intercepts from CAPM, three-factor model, and four-factor model regressions from sorts on size and momentum in emerging markets**
The table presents the summary statistics for regressions on portfolios from sorts on size and momentum for the following regions: Emerging Markets, EM Latin America, EM EMEA, EM Asia, and BRIC. The regressions use local versions of the CAPM (7), three-factor model (8), and four-factor model (9) with local factors. For selected regions and models, the table reports intercepts, a, and t-statistics, $t(a)$, for the intercepts. All returns are in USD. The statistics are computed over the period July 1996 to June 2012.

	a				$t(a)$			
	Low	2	3	High	Low	2	3	High
Emerging Markets: Local CAPM								
Small	0.27	0.72	1.27	0.88	0.53	2.80	5.37	3.15
2	-0.47	0.25	0.79	0.99	-1.07	0.99	3.53	3.17
3	-0.68	-0.14	0.45	0.71	-1.80	-0.72	2.43	2.46
Big	-0.53	-0.14	-0.10	0.29	-1.67	-0.85	-0.70	1.18
Emerging Markets: Local three-factor model								
Small	-0.50	0.28	0.79	0.45	-1.14	1.41	4.59	1.73
2	-0.84	0.03	0.53	0.64	-2.16	0.17	3.11	2.22
3	-0.85	-0.19	0.42	0.55	-2.42	-1.15	2.34	1.89
Big	-0.49	-0.07	0.01	0.31	-1.50	-0.42	0.10	1.27
Emerging Markets: Local four-factor model								
Small	0.22	0.42	0.69	0.07	0.75	2.25	4.10	0.36
2	-0.12	0.16	0.36	0.11	-0.60	0.83	2.33	0.73
3	-0.23	-0.10	0.27	0.06	-1.12	-0.59	1.60	0.34
Big	0.09	0.14	-0.05	-0.08	0.49	1.05	-0.34	-0.50
EM Latin America: Local four-factor model								
Small	0.24	0.38	0.78	0.57	1.00	1.68	2.86	2.42
2	-0.10	-0.27	0.33	-0.13	-0.42	-0.89	1.19	-0.51
3	-0.16	0.17	0.34	0.28	-0.59	0.69	1.19	0.93
Big	-0.01	-0.02	0.25	-0.18	-0.06	-0.09	1.49	-0.93
EM EMEA: Local four-factor model								
Small	0.09	0.34	0.52	0.25	0.37	1.34	2.27	0.97
2	-0.07	-0.17	-0.43	0.45	-0.29	-0.66	-1.49	1.82
3	-0.24	-0.31	-0.25	-0.52	-0.97	-1.13	-0.85	-1.70
Big	0.52	-0.07	-0.38	0.29	2.49	-0.35	-1.58	1.29
EM Asia: Local four-factor model								
Small	0.24	0.12	0.37	-0.03	0.64	0.47	1.57	-0.11
2	-0.07	-0.13	0.37	0.20	-0.31	-0.47	1.96	1.08
3	-0.28	-0.22	0.09	0.20	-1.13	-0.88	0.41	0.94
Big	0.21	-0.15	0.02	0.15	0.86	-0.90	0.11	0.81
BRIC: Local four-factor model								
Small	0.19	0.52	0.43	0.44	0.59	1.78	1.15	1.15
2	0.16	0.00	0.16	0.49	0.61	0.00	0.47	1.98
3	-0.20	-0.15	-0.34	0.01	-0.67	-0.47	-0.93	0.02
Big	0.26	0.11	-0.30	0.02	1.22	0.47	-1.29	0.10

3.7 asset pricing tests with an emerging market model

My results in the previous two sections provide little evidence of integrated global pricing for both Emerging Markets and emerging market regions. But perhaps, emerging markets integrated pricing is present within emerging market regions instead of integrated global pricing. Given the good performance of the local four-factor model in Emerging Markets (keeping microcaps for size-momentum sorts aside), I propose an Emerging Market (EM) model consisting of the risk factors from Emerging Markets as alternative global model. This is analogous to the approach of Fama and French (2012), who construct their global model from regional stock returns. As these regional stocks are solely from developed markets, their global model is basically a developed market model. The tests of the EM model on the emerging market regions are presented in Table 20, Panels A (size-value sorted portfolios) and B (size-momentum sorted portfolios).

The explanatory power for the three EM models regressed on EM Latin American, EM EMEA, and BRIC size-value portfolio returns is low and between 36% and 52%. The average absolute intercepts for the tests are high and range from 0.42 to 0.69. The magnitude of both these statistics is similar to those for the regressions of the standard global models for EM Latin American and EM EMEA. For BRIC, we can see similar absolute intercepts but a higher explanatory power for the EM model. For both, global and EM model regressions, the CAPM, three-factor models, and four-factor models are rejected for EM Latin America; however, at a higher rejection level for the EM model. In contrast to their global counterparts, the EM multifactor models are rejected for EM EMEA excess returns, and vice versa for BRIC excess returns. For EM Asia, I find comparable GRS statistics for the tests of the global and EM models, but the R^2 is significantly higher for the EM models and reach an acceptable level of 85% for the three-factor and four-factor models. Also, the average absolute intercepts are significantly lower, e.g., 0.18 for the test of the EM four-factor model vs. 0.24 for the global four-factor model. The main reason for the good statistics of the EM models on EM Asian returns is the high influence of stocks from EM Asia on EM risk factors. Around 8 out of 10 stocks in the Emerging Market portfolio are from EM Asia. In sum, my results indicate that Emerging Market pricing is not applicable to size-value portfolios of EM Latin America, EM EMEA, and BRIC. For EM Asia, I find support for integrated pricing based on the EM model. This might be due to the fact that the EM sample is highly influenced by EM Asia.

Panel B of Table 20 presents the summary statistics for EM models on size-momentum portfolios. All three EM models for EM Latin America are rejected at the 99% level; however, this is not the case for EM EMEA, EM Asia, and BRIC. Moreover, the standard global models applied in Subsection 3.6.2 are only rejected for EM Latin America and the two multifactor models for BRIC. The average absolute intercepts of the tests of the EM models on all emerging market regions portfolios are high (>0.44), except for the regression of the EM four-factor model on EM Asian portfolios. Similar to the regression of the global models on size-momentum portfolios, I find low explanatory power for all models in EM Latin America, EM EMEA, and BRIC, ranging between 35% and 53%. The average R^2 for the models in EM Asia is higher than for the three other regions; however, I only find an explanatory power of more than 80% for the EM four-factor model. Similar to the tests of the EM four-factor model on size-value portfolios, I find a low average intercept and a high explanatory power for the regressions of the EM four-factor model on size-momentum portfolios in EM Asia. Again, the high influence of stocks from EM Asia on EM risk factors is the reason for this good performance. In sum, my results provide little evidence supporting integrated Emerging Market pricing for size-value and size-momentum portfolios in emerging market regions.

Table 20: **Robustness - Summary statistics for regressions from sorts on size and value, and size and momentum with an Emerging Market model** The table presents the summary statistics for regressions on portfolios from sorts on size and value (Panel A), and size and momentum (Panel B) for the following regions: EM Latin America (EM LatAm), EM EMEA, EM Asia, and BRIC. The regressions use versions of the CAPM (7), three-factor model (8), and four-factor model (9) with RHS factors from Emerging Markets. The GRS statistic tests whether all intercepts for a set of 16 (4×4) regressions are jointly zero; p denotes the respective p-statistic for the GRS statistic; $|a|$ is the average absolute intercept for a set of regressions; R^2 is the average adjusted R^2; $s(a)$ is the average standard error of the intercepts; and $SR(a)$ is the Sharpe Ratio for the intercepts. All returns are in USD. The statistics are computed over the period July 1996 to June 2012.

	EM MODEL					
	GRS	p	$\|a\|$	R^2	$s(a)$	$SR(a)$
Panel A: Size-value portfolios						
EM LatAm						
CAPM	1.78	0.04	0.69	0.49	0.36	0.40
Three-factor	2.07	0.01	0.65	0.50	0.37	0.45
Four-factor	1.96	0.02	0.61	0.50	0.38	0.44
EM EMEA						
CAPM	1.90	0.02	0.51	0.51	0.44	0.42
Three-factor	1.68	0.05	0.50	0.52	0.45	0.40
Four-factor	1.58	0.08	0.42	0.52	0.45	0.40
EM Asia						
CAPM	1.27	0.22	0.28	0.71	0.31	0.34
Three-factor	1.31	0.19	0.21	0.85	0.23	0.36
Four-factor	1.09	0.37	0.18	0.85	0.23	0.33
BRIC						
CAPM	1.72	0.05	0.67	0.36	0.50	0.40
Three-factor	1.24	0.24	0.64	0.50	0.46	0.35
Four-factor	1.05	0.40	0.51	0.51	0.46	0.32
Panel B: Size-momentum portfolios						
EM LatAm						
CAPM	2.30	0.00	0.84	0.48	0.37	0.46
Three-factor	2.80	0.00	0.75	0.50	0.37	0.52
Four-factor	2.48	0.00	0.73	0.50	0.37	0.50
EM EMEA						
CAPM	1.11	0.34	0.50	0.51	0.43	0.32
Three-factor	1.18	0.28	0.53	0.52	0.44	0.34
Four-factor	1.02	0.44	0.44	0.53	0.44	0.32
EM Asia						
CAPM	1.49	0.11	0.51	0.66	0.36	0.37
Three-factor	0.97	0.49	0.45	0.75	0.32	0.31
Four-factor	0.70	0.79	0.14	0.83	0.26	0.26
BRIC						
CAPM	1.49	0.11	0.83	0.35	0.53	0.37
Three-factor	1.25	0.23	0.78	0.43	0.51	0.35
Four-factor	1.08	0.38	0.67	0.48	0.49	0.33

3.8 SUMMARY

Although the importance of emerging market economies and stock markets are constantly rising, only a few studies have investigated value and momentum effects in emerging markets compared to developed markets.

Examining emerging market stock returns in this chapter is threefold. First, I determine the magnitude of standard risk factors on the basis of a broad sample of stocks from 21 emerging market countries in a methodologically consistent way. Second, I explore the size patterns in value and momentum returns of emerging market stock returns. Third, I discuss market integration with a clear focus on Emerging Markets (comprising all 21 emerging market countries) and four emerging market regions (EM Latin America, EM EMEA, EM Asia, and BRIC).

I report only weak statistical evidence for market and size premiums. The market risk premium is only significant for EM Latin America, while the size premium is only significant for EM Asia and BRIC. The value premium is highly significant in the global and Emerging Markets sample as well as in all emerging market regions. The WML premium is also positive for all regions; however, despite the high magnitude, the factor is not as significant as the value factor. Moreover, the three cross-sectional factor premiums have the highest means in the BRIC region. In contrast to global and developed markets, significant value and momentum premiums are present for big stocks, and overall premiums are driven not only by small stocks.

The typical value premiums exist for all size groups in the size-value portfolios. In contrast to Fama and French (2012), the reverse size effect for growth stocks does not exist in emerging markets samples, with exception of EM Latin America. The value-growth spread for emerging markets samples is substantially higher than for developed markets. Besides EM Latin America, the value premium for microcaps is not the highest premium. Furthermore, I find a momentum effect for all size groups in the size-momentum portfolios within all samples - although it is not very strong for the biggest stocks in EM Latin America. I find smaller momentum spreads for the biggest stocks than for the smallest stocks in EM Latin America and BRIC, but also higher spreads in Emerging Markets, EM EMEA, and EM Asia. Thus, I document value and momentum patterns in emerging market size-value and size-momentum portfolios. However, I cannot provide clear evidence that value and momentum patterns decrease with size as in developed markets.

The global models perform poorly for Emerging Markets and the emerging market regions. They primarily fail in explaining returns of size-value and size-momentum portfolios due to high average absolute intercepts and low explanatory powers in the regression results. Therefore, based on the results of this chapter, I have to reject integrated global pricing for all emerging markets samples. Nevertheless, if I substitute global risk factors by local risk factors, results support for the validity of local four-factor pricing, especially in EM EMEA and EM Asia. Also, an alternative global emerging markets model is less successful in explaining the returns of the sub-regions than the local models.

In general, the models applied in this chapter face more problems in explaining size-momentum portfolio returns than in explaining size-value portfolio returns. For size-value portfolios, there is only a marginal difference between the results of the three-factor model and the four-factor model. Thus, if a portfolio without momentum tilts should be priced, the three-factor model is sufficient for accurate pricing. Adding WML is not necessary but does not harm the results. However, the four-factor model is superior when applied to size-momentum portfolios. Microcaps in Emerging Markets and emerging market regions are not as challenging for the models as in developed markets. Only for the size-momentum portfolios in Emerging Markets and for both portfolio sorts in EM Latin America, the models perform significantly better if microcaps are excluded. In sum, local four-factor models are the right choice for pricing diversified emerging market portfolios.

4

IS JAPAN DIFFERENT? EVIDENCE ON MOMENTUM AND MARKET DYNAMICS

Recent evidence for the U.S. indicates that momentum profits are conditional on market dynamics. This chapter documents that the following finding holds for the Japanese market as well: momentum returns are significantly higher when the market stays in the same condition than when it transitions to the other state.[55] This evidence is consistent with the behavioral model of Daniel et al. (1998). Furthermore, market transitions occurred more frequently in Japan compared to the U.S. These results explain why average momentum returns have historically been low in Japan, a fact generally referred to as an empirical failure of momentum. Overall, my findings indicate that different market dynamics, and not different momentum, cause the overall low momentum returns in Japan.

4.1 INTRODUCTION

Past return-based investment strategies, such as the momentum strategy by Jegadeesh and Titman (1993), have been studied intensively by financial economists over the last two decades. Their success has been documented for different countries (Rouwenhorst, 1998, 1999), time periods (Jegadeesh and Titman, 2001), and asset classes (Asness et al., 2013). Thus, momentum is one of the big three anomalies besides size (Banz, 1981) and value (Rosenberg et al., 1985; Fama and French, 1992; Lakonishok et al., 1994).

55 This chapter is based on Hanauer (2014).

There are three main stories that can explain such profitable investment strategies.[56] First, the factors that the strategy is based on are proxies for risk not captured by the suggested underlying asset pricing model.[57] Second, the market is not efficient and the profits are the result of systematic mispricing. Third, the empirical evidence is spurious because of survivorship bias or simply data mining.

In contrast to the size effect,[58] value and momentum have survived most out-of-sample tests. Whereas the debate on the value effect focuses on whether risk (e.g., Petkova and Zhang, 2005; Zhang, 2005) or mispricing (Lakonishok et al., 1994) is the main driver, I regard the abovementioned third argument as motivation for the analysis within this chapter.

Despite the broad evidence of momentum profits around the world, there is one remarkable exception. Several studies argue that momentum strategies fail in Japan as they do not find any significant premium (e.g., Griffin et al., 2003; Fama and French, 2012; Asness et al., 2013) or even observe a negative mean return (Chou et al., 2007). Although these results could be rejected as bad luck, there are other explanations why momentum returns are smaller in Japan or why momentum should not be considered alone. Chui et al. (2010) argue that momentum returns are weaker in countries with low individualism such as Japan or other parts of Asia. Some researchers, such as Fama and French (2012), are skeptical because "it seems [that] the argument could go the other way" (p. 461), and they see the evidence as a chance result. In contrast, Asness (2011) argues that momentum should be studied in a system with value because they are negatively correlated. A combined 50/50 strategy also works in Japan, so he states that "momentum in Japan [...is] the exception that proves the rule" (p. 67). However, the author gives no theoretical explanation for why value and momentum should be negatively correlated.

56 Fama and French (1996) identify these three arguments for the explanatory power of their SMB and HML factors.
57 E.g., the CAPM or the Fama-French three-factor model.
58 See van Dijk (2011) for a comprehensive review of the size effect.

In this chapter, I investigate why momentum strategies on average do not deliver any significant premium in Japan. In contrast to the majority of studies on momentum, I focus on momentum profits in different market dynamics. According to the behavioral model of Daniel et al. (1998), investors' overconfidence is expected to be higher when the market remains in the same state than when it reverses. Therefore, momentum returns should be higher in market continuations than in market transitions. Asem and Tian (2010) provide mixed evidence, because they can present this pattern for the U.S. but not for Japan.

I instead show that market-dynamic conditional momentum is also present in the Japanese stock market by examining a comprehensive and carefully screened dataset. I observe that momentum returns are significantly higher when the market stays in the same condition than when it transitions to the other state. Furthermore, this pattern is more pronounced after periods of poor market performance. A potential explanation for this contrast might be the result of the option-like payoff of the loser portfolio after market declines. However, the question of why momentum on average exhibits no significant premium remains. Assuming that the distribution of market transitions for Japan is the same as in the U.S., the magnitude of momentum premiums would be substantially higher. Overall, my findings indicate that different market dynamics, and not different momentum, cause the overall low momentum returns in Japan. Finally, my results are robust to various specifications and also hold for other countries with low average momentum returns.

My analysis contributes to the existing literature in at least two ways. To the best of my knowledge, I am the first to provide evidence outside the U.S. that momentum returns are conditional on market dynamics. This is consistent with the behavioral model of Daniel et al. (1998). Moreover, my findings explain why average momentum returns have historically been low in Japan, a fact generally referred to as an empirical failure of momentum.

The remainder of this chapter is organized as follows. Section 4.2 introduces an overview of potential sources of momentum profits and Section 4.3 provides details about data and calculation of momentum returns and other risk factors. Section 4.4 presents descriptive statistics about the risk factors, and Section 4.5 shows the main empirical results. Finally, Section 4.6 applies robustness tests, and Section 4.7 concludes.

4.2 SOURCES OF MOMENTUM PROFITS

There is an ongoing debate among researchers about the sources of momentum profits.[59] Models trying to explain momentum profits with market risk (Jegadeesh and Titman, 1993, 2001) or the Fama-French factors (Jegadeesh and Titman, 2001; Fama and French, 1996; Grundy and Martin, 2001) fail.

Besides these standard risk models, some other rational models exist.[60] While these models explain why momentum profits exist, the magnitude of the momentum returns observed (e.g., approximately one percent per month in Jegadeesh and Titman, 1993) would require extreme levels of risk aversion for these models (see Chui et al., 2010).

As a consequence, most academic research focuses on behavioral explanations. Barberis et al. (1998) state that conservatism bias might lead to an initial underreaction to new information, followed by momentum profits. According to Grinblatt and Han (2005), underreaction is also caused by the disposition effect, which leads investors to stick with their past losers and sell their past winners too early. George and Hwang (2004) also provide evidence that anchoring on past prices might cause momentum.

Daniel et al. (1998) suggest a model in which investors receive public signals after trading a stock based on a private signal. If the public signal confirms their private signal, the investors attribute the suc-

59 See, e.g., Jegadeesh and Titman (2011) for an overview.
60 See, e.g., Johnson (2002) or Sagi and Seasholes (2007).

cess to their skills; however, they attribute non-confirming signals to bad luck because of a self-attribution bias. Because of this cognitive bias, the individuals become overconfident about their stock selection skills, and this overconfidence drives momentum.

Hong and Stein (1999) model two groups of investors: newswatchers observing some private information and momentum traders acting only on past prices. The private information diffuses slowly over time, causing some initial underreaction and attracting the momentum traders attention. Thus, they cause momentum and an eventual overreaction.

Based on the evidence in Cooper et al. (2004) that momentum profits exist only after periods of positive market performance, Asem and Tian (2010) develop hypotheses about the magnitude of momentum profits in different market dynamics, according to the models of Sagi and Seasholes (2007), Hong and Stein (1999), and Daniel et al. (1998). The empirical evidence that momentum profits are higher when the market remains in the same condition than when the market reverses is consistent only with the behavioral model of Daniel et al. (1998).

In the model of Daniel et al. (1998), a public signal confirming a trade based on a private signal increases overconfidence, while a disconfirming signal either slightly decreases overconfidence or keeps it constant due to self-attribution. Thus, positive public signals following a "buy" or negative public signals following a "sell" increase overconfidence.[61] Asem and Tian (2010) assume that investors, on average, traded more based on positive private signals when the past market was positive. Consequently, subsequent positive months should drive overconfidence more than subsequent negative months. Analogously, the investors should have traded more based on negative private signals in a period of bad market performance. Subsequent negative months should then drive overconfidence more than subsequent positive months. Thus, overconfidence can also increase in a bear market

61 Note that Daniel et al. (1998) clearly state that confirming negative public signals ("bad news after a sell", p.1842) also drive investor overconfidence.

if the market continues to decline. As a result, I expect higher overconfidence and thus higher momentum profits when the market remains in the same state than when it reverses.

4.3 DATA AND RISK FACTOR CONSTRUCTION

4.3.1 *Data*

The sample of Japanese stocks used in this chapter is derived from Thomson Reuters Datastream (TRD). As Ince and Porter (2006) describe, raw return data from TRD may not be error-free. Following Ince and Porter (2006), Griffin et al. (2010), and Schmidt et al. (2010), I apply several screens to ensure data quality. The static screens ensure that the sample contains only Japanese common equity stocks, as described in detail in Subsection 2.2.1.

This screening process leaves 5,043 unique securities. For these securities, I obtain return data from Datastream and accounting data from Worldscope. All items are measured in JPY. To ensure data quality, I limit my analysis to the period from October 1986 to September 2012.[62] Following Ince and Porter (2006) and Schmidt et al. (2010), I apply several dynamic screens to the monthly return data, as described in Subsection 2.2.2.[63] As a proxy for the risk-free rate, I choose the Japanese one-month interbank rates offered by the British Bankers' Association (BBA).

To qualify for my sample from October of year y to September of year $y+1$, a security needs a valid value for the market capitalization on March 31 and September 30 of year y, a positive book value at the

62 "The base year for the Worldscope Database is 1980, although statistically significant company and data item representation is best represented from January 1985 forward" (Thomson Reuters, 2013c, p.27).

63 Ince and Porter (2006) point out that raw return data from Datastream could especially affect momentum returns. E.g., Datastream repeats the last valid data point, such as the price of a stock, for a delisted stock. This fact could, for example, lead this stock to wrongly appear in the winner portfolio when the overall market is down, as it seems to outperform the market. To avoid this problem, I calculate returns from the total return index and delete all zero returns from the end of the time-series to the first non-zero return.

fiscal year end that falls between April of year $y-1$ and March of year y, and valid stock returns for the previous 12 months. I define book value as common equity plus deferred taxes, if available.[64]

Table 21: **Number of stocks and aggregated market value for Japan**
The table shows the number of stocks in my sample and the aggregated market value (MV) in JPY billion as of end of September of each year y. To qualify for the sample from October of year y to September of year $y+1$, a security needs a valid value for the market capitalization on March 31 and September 30 of year y, a positive book value at the fiscal year end that falls between April of year $y-1$ and March of year y and valid stock returns for the last 12 months.

	No. of stocks	Agg. MV in JPY bn
1986	803	219778
1987	834	305003
1988	953	335724
1989	1136	465079
1990	1443	290533
1991	1826	354128
1992	1953	265671
1993	2018	336555
1994	2068	334565
1995	2132	312112
1996	2246	365046
1997	2300	301875
1998	2857	236879
1999	3048	354811
2000	3081	343739
2001	3199	256912
2002	3288	255374
2003	3382	301259
2004	3406	337329
2005	3523	438577
2006	3611	498760
2007	3751	514021
2008	3814	360887
2009	3718	318430
2010	3633	295723
2011	3552	279304

Table 21 shows the number of stocks in my sample as of the end of September of each year. From the 5,043 unique securities, 4,783 unique securities meet my sample-selection criteria in at least one year. The sample consists of a minimum of 803 stocks in 1986 and a maximum of 3,814 stocks in 2008.

64 This definition is standard in the Fama-French factor literature, see, e.g., Fama and French (1993) or Fama and French (1996).

4.3.2 *Risk factor construction*

I construct five risk factors following the standard procedures of Fama and French (2012) and Jegadeesh and Titman (2001). These factors are the the market factor (RMRF), the size factor (SMB, small minus big), the value factor (HML, high minus low), and the two momentum factors (WML, winner minus losers, and MOM, momentum).

RMRF is the excess return of the market return (RM), a value-weighted return of all sample stocks, over the risk-free rate (RF). I choose the Japanese one-month interbank rate as a proxy for the risk-free rate.

For the construction of the size and value factor, SMB and HML, I follow the procedure of Fama and French (2012), with the exception of the portfolio construction date. The majority of the companies listed in Japan have March 31 as their financial year end.[65] As I wish to ensure that all accounting information is publicly available at the time of portfolio construction, I choose the end of September, instead of June, as the construction date for the book-to-market (B/M) and size portfolios. At the end of September of each year y, all stocks are sorted independently into two size groups, Big (B) and Small (S), and three B/M groups, High (H), Medium (M), and Low (L). According to Fama and French (2012), big stocks (B) represent the top 90% of the aggregate market capitalization at the end of June of year y, while small stocks (S) represent the bottom 10%.[66] B/M is calculated as the book value at the fiscal year end, falling between April of year $y-1$ and March of year y, divided by the market capitalization at the end of March of year y. The breakpoints for the book-to-market ratio are the 30th and 70th percentiles of B/M for the biggest stocks (B), which are also applied to small stocks.

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65 See also Chan et al. (1991) or Daniel et al. (2001).

66 Fama and French (1993) calculate the median for all NYSE stocks but apply this breakpoint to all NYSE, AMEX, and NASDAQ stocks. They want to avoid a high weight of tiny stocks within the size dimension as NYSE stocks have, on average, a higher market capitalization. Fama and French (2012) mention that the NYSE median roughly corresponds to 90% of the aggregate market cap.

At the intersection of the two size and three B/M groups, I construct six portfolios (S/H, S/M, S/L, B/H, B/M, and B/L). Monthly value-weighted returns are calculated for the next twelve months starting from October of year y until September of year $y + 1$. The portfolios are reformed at the end of September of year $y + 1$.

Based on theses portfolios, I construct the monthly time-series of SMB and HML as follows:

$$SMB_t = \frac{(r_t^{S/L} + r_t^{S/M} + r_t^{S/H}) - (r_t^{B/L} + r_t^{B/M} + r_t^{B/H})}{3} \tag{11}$$

and

$$HML_t = \frac{(r_t^{S/H} + r_t^{B/H}) - (r_t^{S/L} + r_t^{B/L})}{2}. \tag{12}$$

In words, the size factor, SMB, is the difference between the average returns of the three small stock and the three big stock portfolios, while the value factor, HML, is the difference between the average return of the two high B/M and the two low B/M portfolios.

Following Carhart (1997) and Fama and French (2012), I also construct WML. Each month t, I sort stocks by their cumulative performance from month $t - 11$ to month $t - 1$ (it is standard to skip the last month t). Again, the momentum breakpoints for all stocks are the 30th and 70th percentiles of lagged performance for the biggest stocks (B). Here, L denotes losers (bottom 30% of lagged return), N denotes neutral (middle 40%), and W denotes winners (top 30%). The intersection of the size and momentum groups results in the six value-weighted portfolios S/L, S/N, S/W, B/L, B/N, and B/W. Similar to the calculation of HML, the momentum factor, WML, based on Carhart (1997), is the difference between the average return of the two winner and the two loser portfolios:

$$WML_t = \frac{(r_t^{S/W} + r_t^{B/W}) - (r_t^{S/L} + r_t^{B/L})}{2}. \tag{13}$$

Additionally, I construct an alternative momentum factor, MOM, according to Jegadeesh and Titman (2001). At the end of each month t, I rank the stocks in my sample based on their cumulative return for month $t-5$ to month $t-1$ and assign the stocks to ten portfolios. Portfolio 10 comprises past winners and portfolio 1 comprises past losers. Each portfolio is held for six months. I calculate value-weighted returns to reduce the effect of small stocks. As in Jegadeesh and Titman (2001), I construct overlapping portfolios; in other words, a momentum decile portfolio in any month holds stocks ranked in that decile from the previous six ranking months. Each monthly cohort is assigned an equal weight in this portfolio. MOM is the return difference between portfolio 10 and portfolio 1.

Besides the raw momentum return, I also calculate the Fama and French (1993) adjusted momentum returns a for each month t as

$$a_t = WML_t - \hat{b}RMRF_t - \hat{s}SMB_t - \hat{h}HML_t, \tag{14}$$

where RMRF, SMB, and HML are the common risk factors, as described above. $\hat{b}$, $\hat{s}$, and $\hat{h}$ are the estimated loadings from a time-series regression of the momentum variable on the common Fama and French (1993) risk factors plus a constant. As momentum usually cannot be explained by the Fama and French (1993) risk factors (see, e.g., Fama and French, 1996), I do not expect my results to be altered by this adjustment.

4.4 BASIC EVIDENCE

This section reports the descriptive statistics of the standard risk factors from October 1986 to September 2012 in Japan. Table 22 shows the summary statistics and correlations. The average return of the market (RM) is only slightly higher than the average risk-free rate (RF), resulting in an equity risk premium (RMRF) that is nearly zero. Fama and French (2012) observe even a negative equity risk premium for a slightly earlier time frame.

There is only a small size premium of 0.1% that is not significantly different from zero (t = 0.49). In contrast, I document the well-known value premium in Japan. The average HML return is 0.68 and 4.64 standard errors from zero.

Similar to Fama and French (2012) and Asness et al. (2013), I cannot find a premium for WML. Moreover, the slightly different methodology for MOM does not change the result. Comparable to Griffin et al. (2003), I observe only a small premium of 0.19% that is not significantly (t = 0.5) different from zero. This evidence leads to the common view that momentum strategies fail in Japan.[67]

The second part of Table 22 shows the correlations of the risk factors. Besides, the naturally high correlations of the two factors depending on the market (RM and RMRF) and on past returns (WML and MOM), the correlations between the other factors are rather small. There is a small negative correlation between RMRF and HML of -0.22 and between RMRF and WML (MOM) of -0.2 (-0.14). We can also see a negative correlation between HML and WML (MOM) of -0.07 (-0.07), but not as negative as in Asness (2011).[68]

67 The contrary evidence of a negative momentum mean return in Chou et al. (2007) can be reconciled with my results because of two major methodological differences. Chou et al. (2007) use equal-weighted momentum portfolios and do not skip one month between portfolio ranking and investment period. Following their approach, the return on WML and MOM would be -0.545% and -0.568% with t-statistics of t =-2.01 and t = -1.83.

68 Changing the month of the market capitalization in the denominator of B/M from March to September would push the coefficient down to a level similar to that in Asness (2011) (-0.55). See also Asness and Frazzini (2013) for a detailed analysis of this alternative specification.

Figure 4: **Cumulative performance of risk factors premiums for Japan**
The figure plots the cumulated performance of the monthly time-series of the market (RMRF), size (SMB), value (HML), and momentum (WML and MOM) factors for Japan. The time-series are computed over the period October 1986 to September 2012.

Figure 4 visualizes the cumulative performance of my risk factors RMRF, SMB, HML, WML, and MOM from October 1986 to September 2012. The chart illustrates the aforementioned results. The equity risk premium is very volatile, and especially in the nineties, we can observe a lot more market transitions in Japan than we would in the U.S. The size premium is positive for the beginning of my sample until the early nineties. This result is consistent with the observation of a positive size premium in earlier studies of the Japanese market, as in Chan et al. (1991) or Daniel et al. (2001). After the early nineties, I document a negative performance for SMB. In contrast, I see a nearly stable value effect, interrupted only by a sharp decline in the cumulative value premium during the tech bubble around the year 2000.

WML and MOM both are highly volatile and correlated. The overall cumulative performance is actually negative. The different signs of the two premiums between Table 22 and Figure 4 are due to differences in the arithmetic and geometric averages. Although there are time periods when momentum strategies work well, such as in the mid two thousands or late nineties, there are also months with sharp momentum crashes. These crashes tend to occur when the market rebounds after some months of decline (growth) as in October 1990 or February 2009 (March 2000).

The following section analyzes this dependency of momentum returns on market dynamics.

Table 22: **Descriptive statistic for risk factors in Japan**
The table reports summary statistics of the market return (RM), the risk-free rate (RF), the excess return of the market over the risk-free rate ($RMRF = RM - RF$), the size factor (SMB), the value factor (HML), and the two momentum factors (WML and MOM). At the end of September of each year y, all stocks are sorted independently into two size groups, Big (B) and Small (S), and three B/M groups, High (H), Medium (M), and Low (L). At the intersection of the two size and three B/M groups, I construct six portfolios (S/H, S/M, S/L, B/H, B/M, and B/L). Monthly value-weighted returns are calculated for the next twelve months starting from October of year y until September of year $y+1$. The portfolios are reformed at the end of September of year $y+1$. The size factor, SMB, is the difference between the average returns of the three small stock and the three big stock portfolios, while the value factor, HML, is the difference between the average return of the two high B/M and the two low B/M portfolios. Following Carhart (1997) and Fama and French (2012), I also construct WML. Each month t, I sort stocks by their cumulative performance from month $t-11$ to month $t-1$ (it is standard to skip the last month t). Again, the momentum breakpoints for all stocks are the 30th and 70th percentiles of lagged performance for the biggest stocks (B). Here, L denotes losers (bottom 30% of lagged return), N denotes neutral (middle 40%), and W denotes winners (top 30%). The intersection of the size and momentum groups results in the six value-weighted portfolios S/L, S/N, S/W, B/L, B/N, and B/W. Similar to the calculation of HML, the momentum factor, WML, based on Carhart (1997), is the difference between the average return of the two winner and the two loser portfolios. Additionally, I construct the momentum factor, MOM, according to Jegadeesh and Titman (2001). At the end of each month t, I rank the stocks in my sample based on their cumulative return for month $t-5$ to month $t-1$ and assign the stocks to ten portfolios. Portfolio 10 comprises past winners and portfolio 1 comprises past losers. Each portfolio is held for six months. I calculate value-weighted returns to reduce the effect of small stocks. As in Jegadeesh and Titman (2001), I construct overlapping portfolios; in other words, a momentum decile portfolio in any month holds stocks ranked in that decile from the previous six ranking months. Each monthly cohort is assigned an equal weight in this portfolio. MOM is the return difference between portfolio 10 and portfolio 1. The statistics are computed over the period October 1986 to September 2012.

	RM	RF	RMRF	SMB	HML	WML	MOM
Mean	0.06	0.15	-0.08	0.10	0.68	0.02	0.19
Std dev	5.57	0.19	5.58	3.68	2.59	4.73	6.66
t-Mean	0.19	13.41	-0.27	0.49	4.64	0.06	0.50
				Correlations			
RM	1.00						
RF	-0.03	1.00					
RMRF	1.00	-0.07	1.00				
SMB	0.00	0.05	0.00	1.00			
HML	-0.22	-0.03	-0.22	0.02	1.00		
WML	-0.21	-0.06	-0.20	-0.25	-0.07	1.00	
MOM	-0.14	-0.04	-0.14	-0.25	-0.07	0.88	1.00

4.5 CONDITIONAL MOMENTUM PROFITS

4.5.1 *Market dynamics*

Following Asem and Tian (2010), I classify each month t the past market as either a BULL market or a BEAR market, depending on whether the past cumulative twelve-month return of the market (RM) is non-negative or negative. Furthermore, I classify month t as a subsequent UP (DOWN) market if the return of the market in month t is non-negative (negative).

Table 23: **Market dynamics and momentum profits in Japan**
The table reports the *WML* means, and monthly Fama and French (1993) adjusted return (FF$-\alpha$) means for different market dynamics in Japan. For each month t, I classify the past market either as a BULL market or a BEAR market, depending on whether the past cumulative twelve-month return of the market (RM) is non-negative or negative. Furthermore, I classify month t as subsequent UP (DOWN) market if the return of the market in t is non-negative (negative). The statistics are computed over the period October 1986 to September 2012.

	Subsequent DOWN markets	Subsequent UP markets	DOWN - UP markets	Both subseq. months
Panel A: Past BEAR markets				
Mean	2.35	-2.88	5.24	-0.00
t-Mean	6.34	-4.54	7.12	-0.00
FF-α	1.49	-1.99	3.48	-0.07
t-FF-α	4.04	-3.46	5.10	-0.20
No. of months	87	71		
Panel B: Past BULL markets				
Mean	-1.35	1.40	-2.74	0.26
t-Mean	-2.84	3.55	-4.45	0.80
FF-α	-1.85	2.36	-4.22	0.61
t-FF-α	-3.74	6.10	-6.70	1.74
No. of months	59	83		
Panel C: Both past conditions				
Mean	0.60	-0.52	1.12	0.02
t-Mean	1.69	-1.32	2.11	0.06
FF-α	-0.05	0.39	-0.45	0.18
t-FF-α	-0.16	1.05	-0.89	0.70

This categorization results in 87 (71) subsequent DOWN (UP) market months following BEAR markets and 59 (83) subsequent DOWN (UP) market months following BULL markets. Compared with the

U.S. market in Asem and Tian (2010), we can observe a rather balanced proportion of the different market dynamics. For the U.S., past BULL markets dominate the sample, with 453 following UP markets and 246 following DOWN markets. The subsequent month is 135 (114) times classified as an UP (DOWN) market after a past BEAR market. This deviating distribution indicates why the average momentum profits could be lower in Japan than in the U.S.

Panel A of Table 23 shows the momentum profits following past BEAR markets. The mean momentum return is 2.35% (t = 6.34) per month when the subsequent market is DOWN and -2.88% (t = -4.54) when the subsequent market is UP. I obtain a difference of 5.24% that is highly significant (t = 7.12). Thus, momentum profits are higher when the market remains negative. The high momentum profits that occur when the market continues to decline are remarkable, as Cooper et al. (2004) argue that momentum profits do not exist after negative market returns. I report an average momentum mean of -0.00% after BEAR markets; however my results demonstrate that this mean is composed of two highly contrary means depending on the subsequent market state. The Fama and French (1993) adjusted returns (FF-α) have the same signs and significance levels as the raw momentum profits.

The results following BULL markets are shown in Panel B of Table 23. The mean momentum return is -1.35% (t = -2.84) when the market reverses and 1.40% (t = 3.55) when it remains in the same state. As stated earlier, the momentum profits depend on the subsequent market development, but the pattern is not as pronounced as after a BEAR market. The difference in momentum returns is -2.74%, with -4.45 standard errors from zero. The Fama and French (1993) adjusted returns (FF-α) lead to the same result.

In Panel C, I distinguish only between the subsequent month and determine that momentum profits are higher for subsequent DOWN market months. The result indicates that the effect after past BEAR markets dominates the effect after past BULL markets. Although the momentum profits in subsequent DOWN markets and the difference in momentum profits are significant, the effect is not as pronounced as for the both different past market regimes. In addition, the Fama and French (1993) adjusted returns (FF$-\alpha$) show only a small difference and are not significant.

At the bottom right corner of Table 23, the outcome of Section 4.4 is shown again. Further, the Fama and French (1993) adjusted returns demonstrates the lack of momentum profits for an unconditional model. The question remains regarding why average momentum returns for Japan are low, although I document the same significant patterns in different market dynamics as in the U.S., where significant momentum returns are observed. I believe that the answer lies in the different distribution of market transitions. As mentioned above, UP markets following past BULL markets dominate in Asem and Tian (2010) for the U.S. This pattern is present only for 28% of the months in Japan, compared with 48% for the U.S. Assuming that the distribution of market transitions for Japan is the same as that in the U.S. and assuming constant premiums for the particular market dynamics, the mean momentum return would be 0.18% per month for WML and 0.40% for MOM.[69] These returns correspond to substantial higher yearly premiums of 2% or 5%. Overall, my findings indicate that different market dynamics, and not different momentum, cause the overall low momentum returns in Japan.

4.5.2 *A potential explanation*

The previous subsection clarified that momentum profits are higher when the market stays in the same condition than when it reverses. As described in Section 4.2, these patterns are consistent with the behavioral model of Daniel et al. (1998). However, the model does

69 Instead, I report 0.02% and 0.19% in Section 4.4.

not provide an explanation for why the pattern is more pronounced after BEAR markets than after BULL markets.

Daniel and Moskowitz (2013) analyze the occurrence of momentum crashes and argue that these crashes follow periods of market declines, when volatility is high and simultaneous with market rebounds. This situation is analogous to my (BEAR, UP) state, where I observe sharp momentum losses. Daniel and Moskowitz (2013) document that momentum portfolios have significant time-varying exposures to the market. By their nature, the market beta of the momentum portfolio is expected to be higher after a past BULL market than after a BEAR market because it is likely that the portfolio is long in high beta stocks and short in low beta stocks. Furthermore, Daniel and Moskowitz (2013) demonstrate that not only do the market betas of the momentum portfolio differ depending on the past market performance but also that after BEAR markets, the beta of the momentum portfolio is significantly lower when the subsequent market is UP. Daniel and Moskowitz (2013) conclude that, "in bear markets, the momentum portfolio is effectively short a call option on the market" (p. 19). Moreover, the loser portfolio is the predominant source of this optionality. They argue that this evidence can be seen as consistent with the theory of Merton (1974) that a common stock is a call option on the value of the firm. Especially after a BEAR market environment, the stocks of the loser portfolio are probably not as deep in-the-money as the stocks of the winner portfolio, and consequently have a stronger option-like behavior.

This so-called optionality is only present after BEAR markets and not after BULL markets. Therefore, momentum returns in the U.S. exhibit a substantially higher sensitivity to the subsequent market development after BEAR markets than after BULL markets. To evaluate whether this evidence may also explain the more pronounced pattern after BEAR markets of the last subsection, I replicate the main model of Daniel and Moskowitz (2013) for Japan.

For the ten momentum portfolios, as described in Section 4.3.2, and the difference of the two extreme decile returns (MOM), I estimate the following regressions:

$$R_t = a + a_B I_B + [b + I_B(b_B + I_U b_{B,U})]RMRF_t + e_t \tag{15}$$

$$R_t = a + a_L I_L + [b + I_L(b_L + I_D b_{L,D})]RMRF_t + e_t \tag{16}$$

In these regressions, I_B and I_L are dummies indicating whether the past cumulative twelve-month return of the market (RM) is negative (I_B) or non-negative (I_L), while I_U and I_D are dummies indicating whether the subsequent month is non-negative (I_U) or negative (I_D). Table 24 shows the results for both regressions.

In Panel A, I estimate the conditional CAPM of equation 15 with I_B as a past BEAR market indicator and I_U as a subsequent UP market indicator. The associated coefficients a_B and b_B indicate whether the intercept and market-beta differ after past BEAR markets while $b_{B,U}$ indicates the extent to which the subsequent UP and DOWN market betas differ after such a past BEAR market.

Analyzing the results for the momentum portfolio, MOM, I determine differences in the market beta depending on the market conditions, consistent with Grundy and Martin (2001) and Daniel and Moskowitz (2013). As expected, I observe a positive beta of 0.185 after BULL markets, while the sign of the beta becomes negative after BEAR markets: if the subsequent market is DOWN, the beta is -0.257 lower, but if the subsequent market is UP, the beta is additional -0.909 (t = -3.76) lower. This results in an overall market beta of $b + b_B + b_{B,U} = -0.981$ if the market reverses after past BEAR markets, but only in a beta of $b + b_B = -0.072$ if the market declines further. The analysis for each of the ten momentum portfolios shows that the prevailing source of this optionality is the loser portfolio.

While the UP market beta of the winner portfolio is 0.304 lower than in subsequent DOWN markets, the loser portfolio beta is 0.605 higher, with a point estimate of 1.72.

In Panel B, I analyze the corresponding model after past BULL markets. In accordance with Daniel and Moskowitz (2013), I do not observe the optionality as described above after BULL markets. While I see a considerable change in the market beta of the momentum portfolio MOM between past BEAR markets and past BULL markets in general (0.760), the difference between subsequent UP and DOWN markets is small and not significant (-0.169). The point estimate for the momentum portfolio is $b + b_L = 0.269$ for subsequent UP markets and $b + b_L + b_{L,D} = 0.1$ for subsequent DOWN markets. Thus, similar to that in the U.S., the momentum strategy in Japan exhibits a substantially higher sensitivity to the subsequent market development after BEAR markets than after BULL markets.

Overall, these results can be interpreted as consistent with the theory of Merton (1974) that a common stock is a call option on the value of the firm. In particular, the stocks of the loser portfolio are not as deep in-the-money after BEAR markets than after BULL markets and therefore exhibit a stronger option-like behavior. This optionality may explain why the patterns, described in the previous subsection, are more pronounced after BEAR markets than after BULL markets.

Table 24: **Momentum portfolio optionality in Japan**
The table reports the results of a regression of the excess return of ten momentum portfolios and the difference of the two extreme decile returns (MOM) on the excess return of the market (RM) and various indicator varibales. In Panel A, I estimate the following regression for each of these portfolios:

$$R_t = a + a_B I_B + [b + I_B(b_B + I_U b_{B,U})]RMRF_t + e_t$$

In Panel B, I estimate the following regression for each of these portfolios:

$$R_t = a + a_L I_L + [b + I_L(b_L + I_D b_{L,D})]RMRF_t + e_t$$

In these regressions, I_B and I_L are dummies indicating whether the past cumulative twelve-month return of the market (RM) is negative (I_B) or non-negative (I_L). I_U and I_D are dummies indicating whether the subsequent month is non-negative (I_U) or negative (I_D). The statistics are computed over the period October 1986 to September 2012.

	1	2	3	4	5	6	7	8	9	10	MOM
Panel A: Past BEAR markets and subsequent UP markets indicator											
a	-0.265	0.054	0.014	0.129	0.033	0.150	0.241	0.336	0.341	0.249	0.514
	(-0.83)	(0.24)	(0.08)	(0.88)	(0.27)	(1.46)	(2.16)	(3.09)	(2.62)	(0.92)	(1.03)
a_B	-0.832	-0.831	-0.510	-0.578	-0.392	-0.473	-0.297	-0.366	-0.127	0.404	1.236
	(-1.47)	(-2.11)	(-1.74)	(-2.22)	(-1.82)	(-2.58)	(-1.50)	(-1.90)	(-0.55)	(0.84)	(1.40)
b	1.034	0.931	0.917	0.896	0.921	0.938	0.965	1.014	1.108	1.220	0.185
	(16.10)	(20.90)	(27.56)	(30.37)	(37.75)	(45.20)	(42.92)	(46.46)	(42.34)	(22.45)	(1.85)
b_B	0.081	0.109	0.102	0.065	0.037	-0.010	-0.044	-0.093	-0.119	-0.176	-0.257
	(0.74)	(1.45)	(1.82)	(1.30)	(0.89)	(-0.29)	(-1.17)	(-2.53)	(-2.69)	(-1.92)	(-1.52)
$b_{B,U}$	0.605	0.441	0.270	0.280	0.132	0.089	-0.027	-0.108	-0.219	-0.304	-0.909
	(3.89)	(4.09)	(3.35)	(3.93)	(2.24)	(1.77)	(-0.49)	(-2.05)	(-3.46)	(-2.31)	(-3.76)
Panel B: Past BULL markets and subsequent DOWN markets indicator											
a	0.292	0.233	0.122	0.193	-0.056	-0.119	-0.117	-0.279	-0.289	-0.044	-0.336
	(0.94)	(1.08)	(0.76)	(1.35)	(-0.48)	(-1.21)	(-1.10)	(-2.68)	(-2.29)	(-0.17)	(-0.69)
a_L	-0.487	-0.178	-0.004	-0.012	0.226	0.249	0.496	0.724	0.671	0.039	0.526
	(-0.81)	(-0.43)	(-0.01)	(-0.04)	(1.01)	(1.31)	(2.43)	(3.63)	(2.76)	(0.08)	(0.56)
b	1.394	1.243	1.144	1.089	1.018	0.969	0.908	0.871	0.888	0.904	-0.491
	(27.17)	(34.85)	(43.33)	(46.25)	(53.23)	(59.62)	(51.93)	(50.94)	(42.71)	(21.19)	(-6.16)
b_L	-0.378	-0.312	-0.254	-0.208	-0.133	-0.025	0.021	0.114	0.209	0.382	0.760
	(-2.85)	(-3.39)	(-3.73)	(-3.41)	(-2.70)	(-0.60)	(0.46)	(2.59)	(3.90)	(3.47)	(3.70)
$b_{L,D}$	0.037	0.001	0.055	0.028	0.072	-0.011	0.072	0.057	0.022	-0.133	-0.169
	(0.18)	(0.00)	(0.52)	(0.29)	(0.93)	(-0.17)	(1.03)	(0.84)	(0.26)	(-0.78)	(-0.53)

4.6 ROBUSTNESS CHECKS

The results in the previous section demonstrated that momentum profits are responsive to current market dynamics. In this section, I will address some alternative specifications and their effects on my results.

4.6.1 *Returns in USD*

Although the choice of the currency should not significantly affect long-short difference returns, such as the momentum portfolios, the market excess return (RM) can differ significantly depending on the currency used to measure it. Thus, the classification into past BEAR (BULL) markets, and subsequent UP (DOWN) markets may differ when returns are measured in USD. In this specification, I use the one-month T-bill, downloaded from Kenneth French's website as the risk-free rate. I show the analogous results for Table 23 in Table 25. Using USD returns results in a slightly different distribution of market states; however, the main results remain the same and are not affected by the choice of the return currency.

4.6.2 *Alternative period*

Asem and Tian (2010) have been unable to confirm their results for Japan. However, I have demonstrated that market-dynamic conditional momentum is also present in the Japanese stock market. Because Asem and Tian (2010) do not provide details about their data process, I am unable to explain this contrary evidence. While I trust my comprehensive and carefully screened dataset, this contrary finding could be the result of different periods covered in the studies. This might indicate that the results are not stable over time. Therefore, I replicate my analysis for the period between October 1986 and

Table 25: **Robustness - Market dynamics and momentum profits in USD**
The table reports the WML means and Fama and French (1993) adjusted return (FF$-\alpha$) means for different market states measured in USD. I classify for each month t the past market either as a BULL market or a BEAR market, depending on whether the past cumulative twelve-month return of the market (RM) is non-negative or negative. Furthermore, I classify month t as subsequent UP (DOWN) market if the return of the market in t is non-negative (negative). The statistics are computed over the period October 1986 to September 2012.

	Subsequent DOWN markets	Subsequent UP markets	DOWN - UP markets	Both subseq. months
Panel A: Past BEAR markets				
Mean	2.37	-2.93	5.30	-0.15
t-Mean	5.21	-4.64	6.81	-0.34
FF-α	1.71	-2.13	3.84	-0.12
t-FF-α	3.75	-3.67	5.20	-0.30
No. of months	75	68		
Panel B: Past BULL markets				
Mean	-0.79	1.26	-2.05	0.36
t-Mean	-1.80	3.21	-3.48	1.20
FF-α	-1.15	2.02	-3.17	0.63
t-FF-α	-2.50	5.27	-5.30	1.96
No. of months	69	88		
Panel C: Both past conditions				
Mean	0.60	-0.50	1.10	0.02
t-Mean	1.65	-1.31	2.08	0.07
FF-α	0.13	0.26	-0.13	0.20
t-FF-α	0.36	0.70	-0.25	0.77

December 2005, which is nearly identical to January 1985 to December 2005 as in Asem and Tian (2010). However, the differences in WML means of 5.40% and -3.34% after BEAR and BULL markets, respectively, are a little more pronounced in this alternative sub-period period.

4.6.3 *Alternative momentum definition*

The momentum strategy definitions of Jegadeesh and Titman (1993), MOM, and the Carhart (1997), WML, are the most common momentum proxies in financial research. To determine whether the alternative definition alters my results, I replace WML with MOM. The MOM means are 2.35%, -2.88%, -1.35%, and 1.40% for (BEAR, DOWN),

Table 26: **Robustness - Market dynamics and momentum profits for an alternative period**
The table reports the WML means and Fama and French (1993) adjusted return (FF$-\alpha$) means for different market states. I classify for each month t the past market either as a BULL market or a BEAR market, depending on whether the past cumulative twelve-month return of the market (RM) is non-negative or negative. Furthermore, I classify month t as subsequent UP (DOWN) market if the return of the market in t is non-negative (negative). The statistics are computed over the period October 1986 to December 2005.

	Subsequent DOWN markets	Subsequent UP markets	DOWN - UP markets	Both subseq. months
Panel A: Past BEAR markets				
Mean	2.32	-3.08	5.40	0.01
t-Mean	4.99	-3.89	5.88	0.01
FF-α	2.10	-2.82	4.92	-0.01
t-FF-α	2.88	-2.78	3.94	-0.02
No. of months	64	48		
Panel B: Past BULL markets				
Mean	-1.84	1.50	-3.34	0.28
t-Mean	-2.86	3.35	-4.26	0.71
FF-α	-1.46	2.74	-4.20	1.21
t-FF-α	-1.46	4.20	-3.52	2.08
No. of months	40	70		
Panel C: Both past conditions				
Mean	0.36	-0.30	0.67	0.00
t-Mean	0.79	-0.67	1.03	0.01
FF-α	0.31	0.68	-0.36	0.51
t-FF-α	0.50	1.14	-0.42	1.18

(BEAR, UP), (BULL, DOWN), and (BULL, UP) states, respectively. Thus, my results are robust to the alternative momentum definition.

4.6.4 *Alternative sentiment definition*

In this chapter, I document that momentum profits in Japan are higher when the market stays in the same condition than when it reverses. This result is consistent with Daniel et al. (1998), who suppose that confirming public information leads to investor overconfidence. Confirming public information is defined as a subsequent positive month after a BULL market and a subsequent negative month after a BEAR market. However it is possible that variables other than market dy-

Table 27: **Robustness - Market dynamics and momentum profits for an alternative momentum variable**
The table reports the MOM means and Fama and French (1993) adjusted return (FF-α) means for different market states. I classify for each month t the past market either as a BULL Market or a BEAR Market, depending on whether the past cumulative twelve-month return of the market (RM) is non-negative or negative. Furthermore, I classify month t as subsequent UP (DOWN) Market if the return of the market in t is non-negative (negative). The statistics are computed over the period October 1986 to September 2012.

	Subsequent DOWN markets	Subsequent UP markets	DOWN - UP markets	Both subseq. months
Panel A: Past BEAR markets				
Mean	2.35	-2.88	5.24	-0.00
t-Mean	6.34	-4.54	7.12	-0.00
FF-α	1.69	-2.25	3.94	-0.08
t-FF-α	3.00	-2.77	3.98	-0.15
No. of months	87	71		
Panel B: Past BULL markets				
Mean	-1.35	1.40	-2.74	0.26
t-Mean	-2.84	3.55	-4.45	0.80
FF-α	-1.14	2.56	-3.69	1.02
t-FF-α	-1.46	4.13	-3.72	2.01
No. of months	59	83		
Panel C: Both past conditions				
Mean	0.60	-0.52	1.12	0.02
t-Mean	1.69	-1.32	2.11	0.06
FF-α	0.24	0.52	-0.29	0.39
t-FF-α	0.48	1.00	-0.40	1.07

namics can also be used as a proxy for investor overconfidence or more general investor sentiment.

Stambaugh et al. (2012) explores how investor sentiment influences the returns of a broad set of anomalies for a U.S. sample. They argue that the primary form of mispricing (due to short selling impediments) is overpricing, and that overpricing is positively related to sentiment. Thus, mispricing should be more present when sentiment is high and for the stocks in the short leg of the trading strategies. Their results show that the returns for each anomaly are higher, and in contrast to the long leg of the strategy, the short legs are more profitable following high sentiment levels.

In this subsection, I follow Stambaugh et al. (2012) to test the effect of sentiment on momentum returns in Japan. Therefore, I use the

Tankan, a short-term business survey of enterprises conducted by the Bank of Japan, as a measure for sentiment. I classify the *WML* return each month as following a high-sentiment month or low-sentiment month. A high-sentiment month is one in which the value of the Tankan large manufacturing index is above the median value of my sample period and vice versa for the low-sentiment months.[70] Table 28 reports the *WML* returns as well as the returns of the long and short leg for high- and low-sentiment months.

Table 28: **Robustness - Alternative sentiment definition**
The table reports average excess returns for the long and short leg of the *WML* factor following high and low sentiment levels. I classify each return as following a high sentiment month or low sentiment month. A high sentiment month is one in which the value of the Tankan large manufacturing index is above the median value of my sample period and vice versa for the low sentiment months. The statistics are computed over the period October 1986 to September 2012.

		High sentiment	Low sentiment	High-Low
Long leg	mean	-0.21	0.23	-0.44
	t-value	-0.44	0.51	-0.68
Short leg	mean	-0.79	0.77	-1.56
	t-value	-1.39	1.38	-1.96
Long-short	mean	0.58	-0.54	1.12
	t-value	1.72	-1.31	2.10

The results show that *WML* returns (row "Long-short") are significantly positive following high sentiment and (insignificantly) negative following low sentiment. The sentiment-related difference in momentum returns is 1.12% per month (t = 2.1). The prevailing source of this difference is the short leg of the strategy. While the (insignificant) difference for the long leg is -0.44, the short leg earns 1.56% (t = -1.96) less following high sentiment than following low sentiment.

My evidence for sentiment-influenced *WML* returns in Japan confirms the results of Stambaugh et al. (2012). Furthermore, the results serve as a robustness check, as I replace my proxy for investor overconfidence with the Tankan survey, a proxy for investor sentiment. Although sentiment and overconfidence are not the same, the results

70 According to Kataoka (2010) the outcome of large manufacturing enterprises, in particular, attracts attention and is used by a large number of studies, e.g., Fatum et al. (2012).

point in the same direction as they demonstrate that, under certain circumstances, momentum profits are also present in the Japanese market.

4.6.5 *International robustness*

Chui et al. (2010) argue that cross-country differences in individualism are related to the average momentum profits in these countries, while I argue that momentum profits depend on market dynamics. I check whether my results also hold in countries with low individualism scores and low average momentum profits. Korea, Taiwan, and Turkey are the only countries besides Japan with negative average momentum profits in Chui et al. (2010), and they are all in the lowest country individualism group. For all three countries, I report significant and positive (negative) momentum premiums after DOWN (UP) markets following past BEAR markets. Except in Turkey, I also see significant and positive momentum profits in UP markets following past BULL markets and negative momentum returns in DOWN markets. Although, the patterns following BULL markets in Turkey are not as pronounced as for the other countries, I still obtain higher momentum profits if the market continues to rise.

Table 29: **Robustness - Market dynamics and momentum profits for other international markets**
The table reports the WML means for different market dynamics in Korea, Taiwan and Turkey. I classify for each month t the past market either as a BULL market or a BEAR market, depending on whether the past cumulative twelve-month return of the market (RM) is non-negative or negative. Furthermore, I classify month t as subsequent UP (DOWN) market if the return of the market in t is non-negative (negative). The statistics are computed over the period July 1995 to June 2012.

Past markets	BEAR		BULL	
Subsequent months	DOWN	UP	DOWN	UP
Panel A: Korea				
Mean	2.71	-5.95	-0.18	1.95
t-Mean	2.64	-3.05	-0.32	2.88
No. of months	46	31	51	64
Panel B: Taiwan				
Mean	1.62	-4.23	-0.55	2.68
t-Mean	2.07	-3.21	-0.73	3.32
No. of months	37	33	55	67
Panel C: Turkey				
Mean	2.00	-3.84	0.15	0.65
t-Mean	1.90	-3.69	0.21	0.97
No. of months	31	42	56	63

4.7 summary

In this chapter, I provide first evidence concerning the profitability of momentum strategies depending on market dynamics in Japan. While several studies conclude that momentum strategies are an empirical failure in Japan, I argue that momentum must be studied conditional on market dynamics.

First, I determine that momentum returns are significantly higher when the market stays in the same condition than when it transitions to the other state. The mean momentum return following a BULL market is -1.35% per month when the subsequent market is DOWN and 1.40% when the subsequent market is UP. Following BEAR markets, the mean momentum return is 2.35% when the market continues to go DOWN and -2.88% when it reverses. These findings are consistent with the behavioral model of Daniel et al. (1998). However, the question remains regarding why momentum on average exhibits no significant premium. Assuming that the distribution of market transitions for Japan is the same as that in the U.S. and assuming constant premiums for the particular market dynamics, the yearly premiums for WML and MOM would be 2% or 5%, respectively. Overall, my results indicate that different market dynamics, and not different momentum, cause the overall low momentum returns in Japan.

Second, I observe that this pattern is more pronounced after periods of poor market performance. I report a difference of 5.24% after BEAR markets but a difference of only 2.74% after BULL markets. A potential explanation of this asymmetry might be the result of the option-like payoff of the loser portfolio after BEAR markets. I do not observe this optionality after BULL markets.

Third, my findings are robust to various specifications and apply to other countries with low average momentum returns.

My results should be of interest to researchers and practitioners alike. They enrich the ongoing debate about the source of momentum profits and show the market dynamics in which momentum strategies would be profitable. Investors should be aware that momentum strategies might be exposed to sharp momentum crashes in BEAR markets if the market rebounds. On the other hand, this risk is rewarded by high momentum profits if the market remains in the same condition. For the Japanese market, my findings indicate that momentum strategies might be more profitable in the future if the overall market performance is more stable than in the past.

5

A NEW LOOK AT THE FAMA-FRENCH MODEL: EVIDENCE BASED ON EXPECTED RETURNS

In this chapter, I test the Fama-French three-factor model for a large international dataset using an alternative proxy for expected returns - the implied cost of capital (ICC).[71] The implied risk premiums of the three factors are all highly significant. Also, the cross-country variation of each of the three factor risk premiums is much smaller compared to their counterparts based on realized returns. For all countries, I find the cross-sectional variation in expected stock returns not only to depend on the stock's market risk but also to be driven by its exposure toward the implied size and value factors. Moreover, even though portfolio intercepts for the three-factor model display significant alphas, they are very small from an economic perspective. I conclude that the Fama-French three-factor model is an appropriate asset pricing model using this alternative proxy for expected returns.

5.1 INTRODUCTION

Asset pricing models typically build on expected returns. Consequently, to test the empirical validity of an asset pricing model, first, one has to find a reasonable proxy for expected returns. Due to the difficulties in observing expectations, realized returns are thus far the most common proxy in empirical studies that test alternative asset pricing models.[72] In this chapter, I apply an alternative expected return measure - the implied cost of capital (ICC).

71 This chapter is based on Hanauer et al. (2014).
72 Their employment started with early and mostly confirmative tests of the CAPM (see, e.g., Black et al., 1972; Fama and MacBeth, 1973).

The three-factor model proposed by Fama and French (1993) is one of the most widely applied multifactor models in both research and practice. By adding mimicking portfolios related to size (SMB) and book-to-market (HML), their model captures cross-sectional patterns better than the CAPM.[73] Although alternative factor models are discussed in the literature (e.g., Hou et al., 2011), it is still seen as the "industry standard" (Subrahmanyam, 2010, p. 35) in empirical asset pricing.

To the best of my knowledge, the explanatory power of the Fama-French three-factor model has only been evaluated using realized returns. Instead, I am the first to validate the Fama-French three-factor model using the ICC. Thus, the main contribution is providing evidence about the appropriate asset pricing model using an alternative expected return proxy. For a well-specified asset pricing model the intercepts should be indistinguishable from zero and it should explain the variation in returns as much as possible.

My expected return estimate, the ICC, which is defined as the discount rate that matches analyst earnings forecasts with the current stock price, has several advantages over observed returns, which have recently come under criticism. First, Elton (1999) argues that realized returns are a poor measure of expected returns because they are notoriously noisy. In contrast, the standard deviation of the ICC is an order of magnitude smaller than the standard deviation of realized returns.[74] Moreover, realized returns cannot be decomposed into a discount rate and a cash flow news part.[75] In contrast, the ICC directly accounts for cash flow news by using time-varying analyst earnings forecasts. Consequently, the ICC reflects only the discount

73 See, e.g., Fama and French (1996).

74 For example, Lee et al. (2009) find for their international sample that the standard deviation ratio of the realized return and the ICC lies in the range of 12.13 (for Canada) and 18.33 (for the U.S.).

75 See Campbell and Shiller (1988); for some more recent applications of the return decomposition approach see Vuolteenaho (2002) and Chen and Zhao (2009).

rate part.[76] Finally, the ICC is conditional on the current state of the economy, and therefore is able to reflect return expectations in line with investors' current risk aversion. For example, Pástor et al. (2008) examine the theoretical relation between the ICC and the conditional expected stock return, and show that the two are perfectly correlated if dividend growth and conditional expected returns follow an AR(1) process. They conclude that the ICC should be useful in capturing time variation in expected returns. In contrast, realized and expected returns are negatively related in the short run since innovations in expected returns cause ex post returns to move in the opposite direction.

These arguments motivated various studies in finance to use the ICC as an expected return estimate in different applications. To name just a few, Claus and Thomas (2001) estimate the equity risk premium with the help of the ICC and find that it is much smaller than estimated with realized returns; Pástor et al. (2008) use the ICC to gain new insights into the time-series relation between the conditional mean and volatility of stock market returns; and Hail and Leuz (2009) employ the ICC to test whether a cross-listing in the U.S. reduces a firm's cost of capital. In summary, both theoretical considerations and empirical evidence indicate that the ICC can shed new light on evidence previously based on realized return data.

In this chapter, I compute firm-level ICC for an international dataset (G-7 countries, i.e., Canada, France, Germany, Italy, Japan, the U.K., and the U.S.) from 1990 to 2011 using analyst earnings forecasts provided by I/B/E/S. I then use the expected risk premiums computed from those ICC and re-run the analysis of Fama and French (1993).

In summary, I find that the Fama-French three-factor model performs very well in explaining the cross-section of expected returns. First, it outperforms the CAPM, which indicates that the risks proxied by the size and value factors are integrated in return expectations

76 Chen et al. (2013) is a recent study that contributes to the return decomposition literature by using the ICC approach. They show that the ICC conveys information similar to the discount rate component in the classical return decomposition approach.

formed by investors. Second, the explanatory power of the model improves when implied as opposed to when realized returns are used. In fact, the alphas of the portfolios are much smaller than those for realized returns and the adjusted R^2 is higher. Third, my results are very robust on a cross-country level. The implied risk premiums of the three factors are all highly significant. Furthermore, the cross-country variation of each of the three factor risk premiums is much smaller compared to their counterparts based on realized returns. This is in line with the argument that risk premiums between developed countries should not vary much due to the possibility of investors to diversify internationally.

However, the ICC approach is not without its own shortcomings. First, the ICC method relies on the assumption that analysts are able to capture, at least partially, market expectations about future cash flows. Furthermore, the I/B/E/S database is biased toward larger firms since those firms are more likely to be tracked by analysts. Finally, there is a multitude of different methodologies to compute the ICC, all resulting in slightly different estimates. While I address those issues in detail in the robustness section, I want to emphasize that I view the analysis within this chapter as a complementary analysis to previous research that uses realized returns. I am not arguing that the ICC is a superior proxy of expected returns but an alternative proxy that is unaffected by points of criticism that realized returns face, while introducing new issues. However, my analysis provides counter evidence against those studies that identify data issues such as survivor bias and data snooping as the main drivers of the significant loadings on the size and value factors in empirical analysis. This chapter uses a completely different proxy for expected returns and applies this proxy to a large international dataset ranging up to December 2011 and still finds significant size and value premiums. It is hard to argue that the evidence based on both realized and implied returns is all due to spurious data. The fact that the Fama-French three-factor model performs well with realized and implied returns, both proxies that are subject to their own set of shortcomings and advantages, is in my opinion a strong indication for the quality of the model.

This chapter is related to other studies that apply alternative proxies for expected returns. Lee et al. (2009) also use an ICC approach to construct firm-level expected returns for a dataset that comprises the G-7 countries and ranges from 1991 to 2000. They follow a two-stage Fama and MacBeth (1973) procedure. In the first stage, they use realized returns to compute factor betas consisting of a world market beta, a country-specific local market factor, and a currency factor. In the second stage, they apply cross-sectional regressions on implied returns to identify risk factors. Their main finding is that idiosyncratic volatility, leverage, size, and the book-to-market ratio have a significant impact on expected returns. For a U.S. sample, Tang et al. (2014) use the ICC to compute expected returns for dollar neutral long-short trading strategies formed on a wide array of anomaly variables. They find that, except for the size and value variables, the implied return differences are all between -0.1% and zero, while they are significantly different from zero based on the realized returns. To the extent that the ICC is a reasonable proxy for expected returns, they conclude that only size and value factors are priced risk factors, while the remaining anomalies are due to unexpected returns. Consequently, mispricing, not risk, is the main driving force of the latter asset pricing anomalies. Finally, Campello et al. (2008) construct firm-specific measures of expected equity returns using corporate bond yields and test which factors are priced when they apply asset pricing tests to this proxy. They find that market beta as well as size and value premiums are positive, while momentum is insignificant.

To some extent, these studies are the starting point of my analysis: Given their findings that expected returns are related to the market, size and book-to-market ratio, can the Fama-French three-factor model explain the cross-sectional variation over time? In other words, while those studies try to identify the factors that drive expected returns, I evaluate their explanatory power via Fama-French time-series regressions. The time-series regression approach has several advantages compared to the cross-sectional Fama and MacBeth (1973) approach. First, I do not have to estimate betas based on realized returns in a first step as in Lee et al. (2009). Besides avoiding an errors-in-variable problem, I would rely on realized returns again. Second, calculating value-weighted portfolio returns puts less weight on small stocks and reduces the impact of single stock return outliers. Finally, while the cross-sectional approach allows to control for multiple variables, the time-series portfolio approach enables me to make reliable statements about the expected returns for a group of stocks with certain characteristics. Thus the cross-sectional approach is suited to identify the drivers of expected returns but the time-series is better suited to measure the resulting expected return differences.

The remainder of this chapter is organized as follows. Section 5.2 introduces the methodology to compute the ICC. Section 5.3 provides details about the data and the implementation of the Fama-French three-factor model. Section 5.4 presents summary statistics, while Section 5.5 shows the main empirical results. Section 5.6 applies common robustness tests and Section 5.7 discusses the implications of the results. Section 5.8 concludes.

5.2 METHODOLOGY TO COMPUTE THE IMPLIED COST OF CAPITAL

All methods to compute the ICC are derived from the dividend discount model:

$$P_0 = \sum_{t=0}^{\infty} \frac{D_t}{(1+r)^t}, \tag{17}$$

where P_0 is the stock price at time 0 and D_t is the dividend at time t. If one assumes that the cost of capital r is constant over time, one can numerically solve it. However, further assumptions about the cash flow pattern have to be made to get an empirical implementable solution, and the various methods to compute the ICC only differ in their assumption of this pattern.

Following recent literature, (see for example Pástor et al., 2008; Lee et al., 2009; Tang et al., 2014) I use the method proposed by Gebhardt et al. (2001, hereafter GLS) as my baseline approach. Their method is based on a residual income model, which decomposes a firm's stock price P_0 into two main parts:[77] the book value per share B_0 and the present value of the residual incomes of all future periods:

$$\begin{aligned} P_0 = \quad & B_0 + \underbrace{\frac{FROE_1 - r_{GLS}}{(1+r_{GLS})}B_0 + \frac{FROE_2 - r_{GLS}}{(1+r_{GLS})^2}B_1}_{\text{explicit forecast period}} + \\ & + \underbrace{\sum_{i=3}^{T-1} \frac{FROE_i - r_{GLS}}{(1+r_{GLS})^i}B_{i-1}}_{\text{transition period}} + \underbrace{\frac{FROE_T - r_{GLS}}{r_{GLS} \cdot (1+r_{GLS})^{T-1}}B_{T-1}}_{\text{terminal value}}, \end{aligned} \tag{18}$$

where $FROE_t$ is the forecasted return on equity (FROE) in period t. For the first three years, this is computed as $FEPS_t/B_{t-1}$, where $FEPS_t$ is the consensus mean I/B/E/S analysts earnings per share forecast of period t. After this explicit forecast period, I linearly fade $FROE_t$ for the next nine years to a target industry return on equity (ROE). I compute this target industry ROE as a rolling industry median over the last three years, considering only firms that have a positive ROE. I define industries based on the Campbell (1996) classification. Finally, I compute the terminal value as a simple perpetuity of the residual incomes after period 12. This implies that any growth after period 12 is value-neutral. I infer the book value by applying clean-surplus-accounting and using a constant future dividend payout ratio PO, i.e., $B_t = B_{t-1} + FEPS_t(1 - PO)$. For firms with a nega-

77 Note that Pástor et al. (2008) and Lee et al. (2009) use a slightly modified version of the GLS method that does not rely on residual incomes.

tive payout ratio, I compute it as the ratio between dividends and 6% of the total assets.

Since I/B/E/S updates its forecasts monthly, this is also the periodicity in which I update the cost of capital estimates. However, the right-hand side of equation 18 exclusively relies on items that refer to the fiscal year-end. To match the price on the left-hand side of the equation with the right-hand side, I discount the price to the fiscal year end. Finally, to be consistent with the asset pricing literature that primarily uses monthly returns, I transform the annual ICC to a monthly one in my empirical analysis.

5.3 DATA, RISK FACTOR CONSTRUCTION, AND REGRESSION MODELS

5.3.1 *Data*

My sample of international stocks is derived from Thomson Reuters Datastream (TRD). As Ince and Porter (2006) describe, raw return data from TRD may not be error-free. Following Ince and Porter (2006) and Schmidt et al. (2010), I apply several data screens to ensure the data quality, especially for the realized return samples. I use Thomson Reuters Datastream's constituent lists to build my dataset for the G-7 countries. To avoid a survivorship bias, I use the intersection of Datastream research lists, Worldscope lists, and dead lists for each country. Following Ince and Porter (2006) and Schmidt et al. (2010), I apply static screens, as presented in Subsection 2.2.1. These screens ensure that my sample comprises exclusively of common stocks of each of the G-7 countries.

This screening process leaves 30,641 unique securities for the U.S. and 25,027 for the other G-7 countries. For these securities, I obtain realized return and market capitalization data from Datastream, accounting data from Worldscope, and the analyst forecasts as well as the share price from I/B/E/S on Datastream. All items are measured in local currency. Because of the international setting of my analysis, and to assure data quality, I have to limit my analysis to the period from July 1990 to December 2011 to get a reasonable number of firms per country.

Following Ince and Porter (2006) and Schmidt et al. (2010), I apply several dynamic screens to the monthly realized return data, as described in Subsection 2.2.2.

To qualify for my full sample from July of year y to June of year $y+1$, I need the market capitalization for the security on June 30 of year y and December 31 of year $y-1$ and a positive book value at the fiscal year end of $y-1$. For the sorting of the stocks for the Fama-French factors and portfolios, I define book value as common equity plus deferred taxes, if available.

As a proxy for the risk-free rate in the U.S., I choose the one-month T-bill rate, downloaded from Kenneth French's website. For the other G-7 countries, to the best of my knowledge, no consistent one-month T-bill rates are available. Therefore, I obtain the one-month interbank rates offered by the British Bankers' Association (BBA) from Datastream.

To compute the ICC, I need the consensus mean one-year, two-year, and three-year ahead earnings forecast as well as the stock price from I/B/E/S. In cases in which the three-year ahead forecast is unavailable, but I/B/E/S provides a consensus long-term growth rate for the firm, I use this rate to infer the three-year ahead earnings forecast from the two-year ahead earnings forecasts. Additionally, if the long-term growth rate is not available, I compute it as the implicit growth rate between the one-year ahead and two-year ahead earnings forecasts. I winsorize growth rates below 2% and above 100%, respectively, and exclude all observations with a negative book value. Finally, I compute the book value per share as the Worldscope common equity divided by the I/B/E/S number of shares. As Hail and Leuz (2009) point out, Worldscope and I/B/E/S data should be compatible because they are both split-adjusted. Nevertheless, I apply common-sense filters to check the correctness of the input data match.

I also obtain the actual dividends and earnings per share (EPS), the ROE, the payout ratio, the fiscal year-end, the earnings announcement date, and the total assets from Worldscope. I need the actual EPS to infer synthetic book values per share from the previous fiscal year-end in cases in which the earnings have been announced, but not the book value. I assume that the annual report date is 120 days after the fiscal year-end.[78] Cases in which both book values and earnings have not been announced yet, the first I/B/E/S earnings forecast refers to the earnings of the previous fiscal-year end and I use this item to infer the book value per share.

Because not all my observations for which I have realized returns are covered by I/B/E/S, I will analyze three different samples in my analysis. The first sample consists of all observations for which the data to compute the Fama-French factors based on realized returns is available. I will refer to this sample as the full sample of realized returns. The second sample is a subset of the full sample and consists of all realized return observations for which an implied return is also available for the same month. To this subset of realized returns I will refer as I/B/E/S sample of realized returns. The third sample consists of the same observations as the second sample, but here I use implied returns instead of realized returns. I will refer to this sample as the I/B/E/S sample of implied returns.

Table 30 shows the number of stocks in the full sample as well as in the I/B/E/S subsample as of end of June of each year. To be in the I/B/E/S sample at least one implied return for the following twelve months has to be available. From the 30,641 (25,027) unique securities in the U.S. (other G-7 countries) remain 14,382 (15,332) unique securities in the full sample and 8,895 (10,448) in the I/B/E/S sample. For the U.S. (other G-7 countries) full sample there are 116,908 (152,739)

78 If the earnings announcement date is not available, I set it equal to the annual report date.

firm-year observations and for the I/B/E/S subsample exist 69,865 (76,945) firm-year observations which corresponds to an average coverage of 60% (50%). As it is more likely that larger firms are covered by I/B/E/S than smaller firms, I compare in Section 5.4 the realized risk premiums (especially for the size and value factors) for the full and the I/B/E/S subsample to validate if the subsample is an appropriate proxy of the total sample. Furthermore, I will analyze the risk premiums for the I/B/E/S sample of implied returns.

5.3.2 *Risk factor construction*

I construct the three risk factors for the realized returns of the full and I/B/E/S sample and for the implied returns of the I/B/E/S sample for all G-7 countries. These risk factors are the market factor (RMRF), the size factor (SMB, small minus big), and the value factor (HML, high minus low).

RMRF is the excess return of the market (RM), a value-weighted return of all sample stocks within a country, over the local risk-free rate (RF). I use the one-month T-bill rate as a proxy for the risk-free rate in the U.S. and one-month interbank rates for the other G-7 countries.

For the construction of the size and value factors, SMB and HML, I follow the standard procedure of Fama and French (1993) with the exception of the choice of the size breakpoints. At the end of June of each year y, all stocks within a country are sorted independently into two size groups, Big (B) and Small (S), and three book-to-market (B/M) groups, High (H), Medium (M), and Low (L). For the full sample, I choose the 80% quantile of the market capitalization at the end of June of year y as breakpoint, but for the I/B/E/S sample I choose the median.[79] B/M is calculated as the book value at the fiscal year

79 Fama and French (1993) calculate the median of all NYSE stocks, but apply this breakpoint to all NYSE, AMEX, and NASDAQ stocks. Schmidt et al. (2010) show that the 80% quantile over all stocks (Fama and French (2006) also use this breakpoint) in the U.S. corresponds roughly to the median of the usually larger NYSE stocks. In Section 5.4, I demonstrate that the choice of this breakpoint leads to risk factors for the U.S. that are highly correlated with the risk factors from the website of Kenneth

end of calendar year $y-1$ divided by the market capitalization at the end of year $y-1$. The breakpoints for the book-to-market ratios for both samples are the 30% and 70% quantiles of B/M. At the intersection of the two size and three B/M groups, I construct six portfolios (S/H, S/M, S/L, B/H, B/M, and B/L). Monthly value-weighted returns are calculated for the next twelve months starting from July of year y until June of year $y+1$. The portfolios are updated at the end of June of year $y+1$. Based on theses portfolios, I construct SMB and HML as follows:

$$SMB_t = \frac{(r_t^{S/L} + r_t^{S/M} + r_t^{S/H}) - (r_t^{B/L} + r_t^{B/M} + r_t^{B/H})}{3}. \tag{19}$$

$$HML_t = \frac{(r_t^{S/H} + r_t^{B/H}) - (r_t^{S/L} + r_t^{B/L})}{2}. \tag{20}$$

In words, the size factor, SMB, is the difference between the average of the three small stock and the three big stock portfolios while the value factor, HML, is the difference between the average of the two high B/M and the two low B/M portfolios.

5.3.3 *Regression models*

In the previous section, I described the construction of the risk factors used on the right hand side of the regression models. In this section, I address the construction of the test portfolios on the left hand side of the regression models as well as the regression models itself.

As in Fama and French (1993), I construct 25 (5×5) size-B/M portfolios for the U.S. at the end of June of each year y. For the other G-7 countries, I built 16 (4×4) instead of 25 size-B/M portfolios since the number of securities is smaller for these countries. Similar to the

French. As the I/B/E/S sample is biased toward larger stocks, I use the median as the breakpoint for the subsample analysis.

construction of the size factor, I choose different size breakpoints than Fama and French (1993) for the size-B/M portfolios of the full sample. Schmidt et al. (2010) determine that the 90%, 80%, 70%, 60% quantiles of the market capitalization of all the U.S. stocks correspond roughly to the quintiles of the NYSE stocks. I choose these breakpoints for the U.S. and the 89%, 75%, 62% quantiles for the other G-7 countries. The size breakpoints for the I/B/E/S sample are the quintiles (quartiles) of the market capitalization for the U.S. (other G-7 countries), as larger stocks are more likely covered by I/B/E/S. The B/M breakpoints are the quintiles (quartiles) of the book-to-market ratios for both samples as in Fama and French (1993). The 25 (16) portfolios for each country are constructed at the intersection of the 5×5 (4×4) independent sorted size-B/M groups.[80] Monthly value-weighted returns are calculated for the next twelve months and the portfolios are updated at the end of June of year $y + 1$.

Starting with the CAPM, I estimate the coefficients of the one-factor model presented in equation 21:

$$R_{it} - RF_f = a_i + b_i RMRF_t + e_{it}. \tag{21}$$

Afterwards, I estimate the coefficients of the Fama-French three-factor model presented in equation 22:

$$R_{it} - RF_t = a_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + e_{it}. \tag{22}$$

I calculate Newey and West (1987) robust standard errors to adjust for autocorrelation and heteroskedasticity. I use 3 Newey-West lags for realized returns and, as in Pástor et al. (2008), 12 Newey-West lags for implied returns. To discuss the quality of the models, I analyze the regression results in two steps. First, I consider the adjusted

80 I will refer to theses portfolios as Fama-French portfolios and mark them corresponding to their size and book-to-market equity with $1-1$ ("Small-Low"), ..., $1-5$ ("Small-High"),..., $5-1$ ("Big-Low"),..., $5-5$ ("Big-High").

R^2 of the model. Second, in a model containing all relevant risk factors, the intercepts a_i should not be different from zero. I consider the a_i separately as well as jointly. For the jointly analysis I use the F-statistic of Gibbons et al. (1989, hereafter GRS). However, the GRS test assumes that the regressions residuals are independent and identically distributed. While this assumption maybe true for realized returns, it is critical for implied returns due to their high persistence. Thus the results should be interpreted with caution.

Table 30: **Number of stocks for G-7 countries**
The table shows the number of stocks in the full sample as well as in the I/B/E/S subsample as of end of June of each year y for G-7 countries. To qualify for our full sample in year y, I need the market capitalization for the security on June 30 of year y and December 31 of year $y-1$, and a positive book value at the fiscal year end of $y-1$. To be in the I/B/E/S sample at least one implied return for the following twelve months has to be available in addition to the former requirements.

	Full sample							I/B/E/S sample						
	US	JP	CN	UK	FR	BD	IT	US	JP	CN	UK	FR	BD	IT
1990	2487	1223	252	1193	397	304	181	1790	457	187	788	246	139	109
1991	2498	1610	277	1226	478	344	189	1759	561	197	829	270	226	142
1992	2819	1954	284	1232	485	361	192	1987	612	205	857	262	267	150
1993	2984	2030	289	1199	486	387	191	2196	625	204	848	257	273	147
1994	3336	2096	308	1225	497	443	180	2433	1077	216	882	282	291	142
1995	4494	2204	315	1266	498	449	179	3170	1073	223	917	310	301	135
1996	5004	2270	350	1262	487	461	184	3563	1415	264	1017	313	291	133
1997	5683	2338	373	1478	617	554	188	4062	1479	291	1147	372	342	139
1998	6153	2393	395	1583	690	588	191	4134	1358	300	1148	403	349	143
1999	7131	3123	594	1515	759	658	202	4037	1690	375	1078	432	370	148
2000	7588	3203	758	1422	787	778	215	3690	1772	411	1013	414	349	151
2001	7361	3282	853	1494	838	900	261	3494	1324	390	968	388	439	179
2002	6686	3477	894	1510	816	865	265	3282	1376	431	851	369	386	174
2003	6275	3523	1036	1462	752	770	257	3332	1336	516	828	353	299	171
2004	6083	3586	1102	1390	703	708	245	3387	1423	576	872	336	284	168
2005	6120	3710	1198	1494	678	699	249	3510	1485	644	971	367	305	173
2006	6102	3823	1967	1656	697	740	260	3538	1445	764	980	378	328	190
2007	6096	3936	2084	1794	754	825	272	3478	1403	819	1037	415	411	202
2008	6042	4000	2242	1767	784	860	282	3465	1397	779	1069	425	456	215
2009	5617	3933	2336	1607	762	825	273	3291	1342	742	1016	413	481	198
2010	5258	3805	2314	1441	710	785	261	3261	1430	787	965	408	461	192
2011	5091	3705	2371	1347	672	733	259	3006	1050	759	869	372	372	179
Sum	116908	65224	22592	31563	14347	14037	4976	69865	27130	10080	20950	7785	7420	3580
#Stocks	14382	4825	3473	3676	1484	1392	482	8895	3477	1678	2825	994	1052	422

5.4 DESCRIPTIVE STATISTICS

5.4.1 *Implied cost of capital estimates*

My empirical analysis is based on implied excess returns per month, which I will also present further below. First, however, I want to show summary statistics for the monthly time-series of the yearly ICC estimates. Since the ICC approach is still rather new and not as well established as realized returns, I believe this gives the reader a better understanding of its characteristics.

Table 31: **Descriptive statistics of implied cost of capital**
The table shows the summary statistics for the monthly time-series of the equally (Panel A) and value weighted (Panel B) annualized implied cost of capital for G-7 countries. The statistics are computed over the period July 1990 to December 2011. Furthermore, I report the average number of monthly observations for which an implied cost of capital estimate is available for each country at the bottom of the table.

Country	US	CN	BD	IT	JP	UK	FR
Panel A: Equally-weighted time-series							
Mean	10.26	10.56	9.49	8.90	5.84	13.01	11.03
StDev	1.16	1.63	2.34	2.17	2.04	2.20	1.80
Min	8.24	7.53	5.82	4.85	2.82	9.97	7.47
Max	14.36	17.47	15.47	15.05	11.61	19.59	16.05
Panel B: Value-weighted time-series							
Mean	8.52	8.91	7.90	8.31	4.84	10.31	9.49
StDev	1.18	1.17	2.04	2.60	1.82	2.04	2.05
Min	6.19	7.06	4.70	3.24	2.32	7.27	5.47
Max	11.96	12.42	13.65	15.56	9.39	16.56	14.08
Panel C: Average number of observations							
NrObs	2887	406	313	148	1095	833	328

Table 31 presents the summary statistics of the ICC estimates for each country.[81] The average equally weighted ICC varies from 5.84% in Japan to 13.01% in the U.K. In line with other studies that compute the ICC, the value-weighted estimates are consistently lower than their equally weighted counterparts, which is a first indication that I may have a size effect in the data.

81 I thank Christoph Jäckel for providing the actual ICC data.

Figure 5: **Time-series characteristics of the implied cost of capital for the U.S.**
The figure plots the monthly time-series of the equally and value-weighted implied cost of capital for the U.S. The statistics are computed over the period from 1990 to 2011.

Note that the standard deviation lies in the range of 1.16% and 2.34%. These values are similar to those presented by Lee et al. (2009) and an order of magnitude smaller than those based on realized returns.

Figures 5 and 6 show the monthly time-series of the equally and value-weighted ICC estimates for the U.S and the other G-7 countries, respectively. Across all countries, investors expected high equity returns during the 2008/9 financial crisis. This rise of the ICC was most pronounced for the U.K. firms, most probably because the U.K. with its big financial industry was hit particularly hard by the cri-

Figure 6: **Time-series characteristics of the implied cost of capital outside the U.S.**
Each panel plots the monthly time-series of the equally and value-weighted implied cost of capital for the given country. The statistics are computed over the period from 1990 to 2011.

sis.[82] Also, the ICC catches country-specific events such as the nuclear melt-down in Japan that resulted in an increase of the expected equity return of roughly 1.3 percentage points from February to March 2011. Another example is the strong increase of the German, French, and particularly the Italian ICC at the end of the sample period in the wake of the recent European sovereign crisis.

In totality, the preliminary statistics about the ICC estimates exhibit their main advantageous characteristics: they are able to capture time variation in expected returns and are far less noisy than realized returns. This makes me confident about my approach to use the ICC as an expected return proxy.

5.4.2 *Summary statistics of risk factors*

Table 32 reports summary statistics of the market return (RM), the risk free rate (RF), the excess return of the market over the risk free rate ($RMRF = RM - RF$), the size factor (SMB), and the value factor (HML) for the G-7 countries from July 1990 to December 2011. In Panel A, I show the arithmetic means and t-values of realized returns for my full sample, whereas in Panel B, I only use the subsample of realized returns for which also an implied return is available for the same month (I/B/E/S sample). In Panel C, I report the statistics of implied returns for this subsample.

The risk free rates are ranging from 0.11% per month for Japan to 0.45% for the U.K. and are all significantly different from zero.

The realized market returns for my full sample in Panel A are positive in six of the G-7 countries ranging from 0.44% for Italy to 0.96% for Canada per month, while Japan has a negative market return of -0.18% per month. The negative return on Japanese stocks is evidence of a period of bad luck for investors. However, it reemphasizes Elton's

82 For instance, Panetta et al. (2009) argue that the very high outlays of the British government – they reached 44% of the British GDP – were due to the large banking system compared to the real economy and its dependence on large financial institutions.

argument that realized returns are a poor proxy of return expectations: assuming that investors in Japanese stocks expected negative returns over the last twenty years is inconsistent with finance theory.

The stock returns result in positive monthly equity risk premiums in six of the G-7 countries ranging from 0.01% for Italy to 0.61% for Canada, but only for Canada (t = 2.44) and the U.S. (t = 1.94) they are significantly different from zero. Therefore, my results are rather imprecise, similar to Fama and French (2012) who are analyzing a similar period for North America, Europe, Japan, and Asia-Pacific ex Japan. However, they find a higher equity premium for Europe, which is probably due to the fact that they use dollar market returns over the T-bill rates, which are on average smaller than the interbank lending rates.

I do not find a significant positive size premium in my results. Germany has the only significant size premium, but here it is negative with -0.45% per month. The other average SMB returns are statistically insignificant and show mixed signs. A more homogeneous picture exists for the value premium. The monthly averages of the value factors range from 0.22% for Italy to 0.81% for Germany and are significant for four of the seven countries.

Comparing the U.S. risk factors from my full dataset with the counterparts for the same period, downloaded from Kenneth French's website, shows that the risk premiums are quite similar. On average, the value weighted excess returns of the market yield 0.51% and 0.53% per month, with an almost perfect correlation of 1.00 (rounded value). Although I calculate the size breakpoints as the 80% quantile over all stocks and not as the median of all NYSE stocks such as Fama and French (1993), the means of the size factors are very close. The average monthly premium in Kenneth French's dataset is 0.21% and 0.17% in the full sample. The correlation coefficient between the two size factors is 0.98. A similar difference exists for the value factor, HML. The average value premium is 0.32% per month, while the premium provided by Kenneth French yields only 0.28%.

Despite this deviation, the correlation coefficient of 0.96 is still very high. Altogether, I show that the data screens described in Section 2.2 and choice of breakpoints for the full sample lead to risk factors that are very close to the factors obtained from Kenneth French's website. This suggests that the risk factor constructions steps, as described in Section 2, are appropriate to ensure data quality.

In Panel B, I show summary statistics for the subsample of realized returns of the I/B/E/S sample. In general, these are stocks with higher market capitalization. As the market return and market excess return are value-weighted, I only observe small differences to the values in Panel A. Because of the definition of the size factor and the different breakpoints for the two samples, I find the biggest differences of the monthly averages for the size factor, SMB. For instance, the value for the U.S. doubles and the sign of the factor for Canada switches. In contrast, the significant negative size premium for Germany continues to exist. The premium of the value factor, HML, remains positive in all G-7 countries, although the monthly average or the significance of the value factors are, with the exception of Italy, smaller for the I/B/E/S sample than for the full sample, which indicates that the value premium for developed markets decreases with firm size. Fama and French (2012) and Loughran (1997) report similar results.

Therefore, the results for realized returns for the full sample on the one hand and the I/B/E/S sample on the other are fairly similar. For both samples, the value premiums are consistently positive for all countries and the market excess returns of the two samples are almost identical. I only observe noteworthy differences for the size factor, but even here the sign mostly remains the same. Therefore, I conclude that the subsample captures the characteristics of the full sample reasonably well. Furthermore, the tilt of my sample toward larger firms should makes it more difficult to find meaningful cross-sectional patterns because I reduce the variation in the cross-section and I limit my analysis to larger firms.[83]

When I consider implied instead of realized returns of the I/B/E/S sample in Panel C, I document much more consistent risk premiums.[84] The risk premiums for all the countries are positive and significant. The market risk premium lies between 0.20% for Italy and 0.40% for the U.S. and France. The monthly average of the size factor ranges from 0.07% for Japan and Italy to 0.20% for the U.K. Although the size premiums are economically small (except for the U.K.), they are all statistically significant. The highest value premium exists for Germany with 0.28% per month and the smallest value exists for the U.K. with 0.16% per month. Again, all value premiums are highly statistical significant and also economically relevant (value premiums of 2%-3% per year).

My findings confirm the results of Tang et al. (2014) for the U.S. that the implied premiums for the SMB and HML factors are highly significant and positive. Furthermore, this result also holds for international data. Compared to realized risk premiums, implied returns give much more precise estimators for the risk premiums, because they are both highly significant and fairly homogeneous across countries. This is in line with the argument that risk premiums between developed countries should not vary much due to the possibility of investors to diversify internationally. According to my data, risk premiums of 3% to 5% per year for the market, of 1% to 2% for the size factor, and of 2% to 3% for the value factor appear reasonable.

Given these findings for the implied returns of the value and size factors, I turn now to asset pricing tests. Therefore I will verify the link between returns and firm specific characteristic through time-series regressions. Furthermore, I will examine if adding the two factors to the CAPM will improve the explanatory power of the model.

83 E.g., Fama and French (2012) report that value premiums in developed market stock returns decrease with size.

84 As implied risk returns are highly persistent, their t-statistics are based on Newey and West (1987) robust standard errors to adjust for autocorrelation and heteroskedasticity. As in Pástor et al. (2008), I use 12 Newey-West lags.

Table 32: **Descriptive statistics for risk factors in G-7 countries**
The table reports summary statistics of the market return (RM), the risk free rate (RF), the excess return of the market over the risk free rate (RMRF = RM − RF), the size factor (SMB), and the value factor (HML) for the G-7 countries. The statistics are computed over the period July 1990 to December 2011. In Panel A, I show the arithmetic means and t-values of realized returns for the full sample, whereas in Panel B, I only use the subsample of realized returns for which also an implied return is available for the same month (I/B/E/S sample). In Panel C, I report the statistics of implied returns for this subsample. For implied returns, t-statistics are based on Newey and West (1987) robust standard errors to adjust for autocorrelation and heteroskedasticity up to 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Country	RM	[t]	RF	[t]	RMRF	[t]	SMB	[t]	HML	[t]
Panel A: Realized returns of full sample										
US	0.81***	2.95	0.28***	25.91	0.53*	1.94	0.17	0.80	0.32	1.47
JP	-0.18	-0.52	0.11***	9.86	-0.28	-0.82	-0.18	-0.98	0.62***	3.53
CN	0.96***	3.85	0.35***	28.34	0.61**	2.44	0.01	0.07	0.33	1.46
UK	0.72***	2.76	0.45***	30.45	0.27	1.05	-0.10	-0.41	0.49**	2.37
FR	0.66**	2.07	0.35***	24.10	0.31	0.96	0.01	0.06	0.40*	1.69
BD	0.54*	1.73	0.33***	26.64	0.21	0.68	-0.45**	-2.34	0.81***	3.61
IT	0.44	1.11	0.44***	22.80	0.01	0.02	-0.24	-1.24	0.22	1.04
Panel B: Realized returns of I/B/E/S sample										
US	0.83***	3.00	0.28***	25.91	0.55**	2.00	0.36	1.45	0.24	1.15
JP	-0.15	-0.42	0.11***	9.86	-0.25	-0.72	-0.00	-0.00	0.53***	2.88
CN	0.99***	3.98	0.35***	28.34	0.64**	2.58	-0.00	-0.00	0.33	1.29
UK	0.74***	2.83	0.45***	30.45	0.30	1.13	-0.05	-0.21	0.34*	1.73
FR	0.66**	2.00	0.35***	24.10	0.31	0.93	0.01	0.04	0.37	1.44
BD	0.53	1.46	0.33***	26.64	0.21	0.57	-0.69***	-2.80	0.60**	2.35
IT	0.45	1.11	0.44***	22.80	0.01	0.04	-0.26	-1.18	0.36	1.59
Panel C: Implied returns of I/B/E/S sample										
US	0.68***	35.77	0.28***	25.91	0.40***	8.95	0.09***	5.97	0.21***	15.38
JP	0.39***	12.84	0.11***	9.86	0.29***	5.52	0.07***	5.93	0.16***	18.75
CN	0.71***	39.25	0.35***	28.34	0.36***	8.99	0.13***	7.88	0.18***	9.94
UK	0.82***	25.12	0.45***	30.45	0.37***	6.10	0.20***	7.60	0.26***	14.04
FR	0.75***	22.48	0.35***	24.10	0.40***	7.51	0.11***	5.72	0.25***	16.36
BD	0.63***	18.70	0.33***	26.64	0.31***	4.62	0.13***	5.45	0.28***	20.00
IT	0.64***	16.66	0.44***	22.80	0.20**	2.44	0.07***	4.34	0.25***	12.81

5.5 EMPIRICAL RESULTS

This section contains the results of time-series regression tests of the CAPM and the Fama-French three-factor model for the G-7 countries. Tables 33 and 34 report detailed statistics of implied returns of the 25 (5×5) portfolios and their regression results based on the equations (21) and (22) for the U.S. In Table 35, I show the summary statistics for realized and implied returns of the G-7 countries.

Table 33: **CAPM regression of implied returns for the U.S.**
The table reports detailed statistics of implied returns for the U.S. Panel A summarizes the dependent returns of the 25 (5×5) value-weighted size-B/M portfolios. Panel B reports the regression results of the CAPM. Newey and West (1987) robust standard errors are used to adjust for autocorrelation and heteroskedasticity up to 12 lags. The regression R^2 and the residual standard error $s(e)$ are adjusted for degrees of freedom. The statistics are computed over the period July 1990 to December 2011.

	Book-to-market equity (B/M)									
Size	Low	2	3	4	High	Low	2	3	4	High
	Panel A: Average monthly excess returns									
	Mean					Standard deviation				
Small	0.59	0.54	0.57	0.61	0.69	0.21	0.18	0.19	0.18	0.18
2	0.47	0.49	0.53	0.57	0.67	0.19	0.17	0.17	0.17	0.18
3	0.40	0.46	0.51	0.55	0.64	0.16	0.17	0.17	0.18	0.18
4	0.37	0.43	0.49	0.54	0.60	0.17	0.17	0.17	0.17	0.19
Big	0.30	0.40	0.46	0.52	0.59	0.21	0.21	0.22	0.20	0.21
	Panel B: $R_{it} - RF_t = a_i + b_i RMRF_t + e_{it}$									
	a					$t(a)$				
Small	0.33	0.25	0.27	0.31	0.42	4.82	5.68	5.59	6.70	7.79
2	0.16	0.19	0.23	0.29	0.38	3.68	5.75	6.34	7.13	6.81
3	0.12	0.15	0.20	0.25	0.35	3.95	5.25	5.97	6.19	7.25
4	0.05	0.12	0.19	0.23	0.27	2.06	4.22	5.66	6.31	7.02
Big	-0.10	0.00	0.05	0.14	0.24	-13.90	0.10	1.76	4.85	6.75
	b					$t(b)$				
Small	0.66	0.72	0.73	0.74	0.66	5.08	8.24	8.47	9.23	6.67
2	0.77	0.72	0.75	0.70	0.70	10.21	12.34	11.65	9.86	6.99
3	0.70	0.77	0.77	0.76	0.72	14.34	16.89	13.38	10.59	8.30
4	0.78	0.78	0.73	0.77	0.82	18.26	15.77	12.00	11.75	11.28
Big	1.00	1.00	1.01	0.92	0.87	55.20	33.73	18.14	14.02	13.91
	R^2					$s(e)$				
Small	0.44	0.71	0.70	0.74	0.61	0.16	0.10	0.10	0.09	0.11
2	0.73	0.81	0.84	0.78	0.67	0.10	0.07	0.07	0.08	0.10
3	0.81	0.88	0.88	0.83	0.72	0.07	0.06	0.06	0.07	0.09
4	0.89	0.90	0.87	0.87	0.82	0.06	0.05	0.06	0.06	0.08
Big	0.99	0.98	0.94	0.93	0.81	0.02	0.03	0.05	0.05	0.09

Panel A of Table 33 summarizes the dependent returns of the 25 (5×5) value-weighted size-B/M portfolios. The average implied excess returns for the U.S. are monotonically decreasing with size and (with the exception of Portfolio $1-1$) monotonically increasing with book-to-market equity. Relative to realized returns (see, for instance, Fama and French, 2012), the standard deviations are much smaller. Panel B reports the regression results of the empirical version of the CAPM for the implied returns for the U.S. As mentioned before, if the one-factor model in equation (21) describes expected returns, the intercepts should be close to zero. However, the intercepts are mostly positive with values up to 0.42%. In particular, the model leaves a large positive unexpected return for the portfolios in the smallest size quintile or biggest B/M quintiles. Additionally, the intercepts are both statistically and economically significant. For instance, Portfolio $1-5$ has an annualized intercept of about 5%, more than 7 standard errors from zero. The average absolute intercept amounts to 0.21% per month or more than 2% per year.

The betas ranging from 0.66 to 1.01 tend to be smaller for portfolios in the smaller size quintiles and are all highly significant. However, some variation is left for factors other than the market. The average R^2 is 0.81, but especially for small stock and high B/M portfolios the R^2 are less than 0.8. The R^2 for portfolio $1-1$ is only 0.44 and the maximum R^2 of 0.99 exists for portfolio $5-1$.

Adding SMB and HML to the regression in Table 34 results in an increase of the average R^2 from 0.81 to 0.94. Portfolio $1-1$ has still the lowest R^2, but rises from 0.44 to 0.74. Only two of the 25 portfolios have an R^2 lower than 0.9 for the three-factor model. The increase in the R^2 is a result of the strong slopes on SMB and HML. 21 portfolios have t-values greater than 3 for the size factor. The slopes on SMB are also clearly related to size. In every B/M quintile the coefficients monotonically decrease from small to large stocks.

Similarly, the slopes on HML are related to book-to-market equity. In every size quintile, the coefficients monotonically increase from the lowest B/M to the highest B/M quintile (with the exception of Portfolio $1-1$). Except for the two lowest B/M quintiles, where most of the slopes pass from negative to positive, the coefficients of the value factor are highly significant. There is another interesting effect when adding the size and value factors compared to Table 33. The slopes on the market return factor are now ranging from 0.9 to 1.14; especially the betas in the smallest size quintiles are now much closer to one.

Therefore, how does the Fama-French three-factor model describe the cross-section of average returns, i.e., are the intercepts in Table 34 indistinguishable from zero? The answer is twofold: on the one hand, about half of the intercepts are still significantly different from zero. Again, those high t-values are driven by the low standard deviation of the expected return estimate, which allows for much sharper inferences. On the other hand, they are very small in economical terms. Specifically, the intercepts range from -0.09 to 0.02 with an average absolute value of 0.04, which is much lower than 0.21 for the one-factor model. In summary, the Fama-French three-factor model explains expected returns very well and leaves little unaccounted for.

This finding also holds internationally, as can be seen from Table 35, which summarizes the CAPM and Fama-French three-factor model (FF3FM) regressions to explain excess returns on the 5×5 (4×4) size-B/M portfolios for the U.S. (other G-7 countries). I report the average adjusted coefficient of determination R^2, the average absolute value of the intercepts, and the Gibbons et al. (1989) GRS statistic for 25 (16) portfolios in each country and for the three samples. Thus, I compare the explanatory power of the CAPM and the Fama-French three-factor model for both realized and expected returns.

Panel A shows the results of the full sample for each country. The average R^2 in the CAPM regressions ranges from 0.53 for Germany to 0.76 for Japan. Adding SMB and HML to the model increases the adjusted R^2 for every country. The coefficient of determination ranges now from 0.77 for Germany and Canada to 0.90 for Japan. The average absolute values from the CAPM intercepts of the Fama-French portfolios range from 0.17 for Canada to 0.37 for Germany. For the Fama-French three-factor model all intercepts decrease; to a range between 0.12 for Japan and 0.26 for Italy. Although the hypothesis that all intercepts are jointly zero has to be rejected for nearly every country and for both models, an improvement of the GRS test statistic value is reported for every country beside Italy.

The statistics for the realized returns for the subsample in Panel B show a similar picture as Panel A. All average R^2 are increasing and all average absolute intercepts are slightly decreasing for the Fama-French three-factor model compared to the CAPM. The GRS statistic for the Fama-French three-factor model on the I/B/E/S subsample improves for all countries beside Canada and France compared to the full sample. This evidence confirms the results in Fama and French (2012) that the three-factor model does a good job in explaining returns of portfolios when microcaps are excluded. Nevertheless, the alphas for both the full and the subsample are economically relevant.

When we look at the summary statistics for the implied returns, we can see the same results for the other G-7 countries as for the U.S. discussed at the beginning of the section. The average CAPM R^2 are higher than their counterparts for the realized returns and ranging from 0.80 for the U.K. to 0.96 for Japan. When I add the value and size factors, the R^2 are even increasing to a range of 0.88 for Canada to 0.99 for Japan. Furthermore, the absolute average intercepts are much lower than their counterparts for the realized returns. For the CAPM, the values lie between 0.21% for the U.S. and U.K. and 0.06% for Japan. Adding SMB and HML to the model pushes the average absolute intercepts economically close to zero. The maximum value exists with 0.07% for Germany. The values for the other countries are around 0.05% per month or below, which corresponds to a yearly value of 0.5% or below. As mentioned above, the intercepts' standard errors for the implied returns are much smaller than for the realized returns. Therefore, despite their economically low values, some intercepts in Table 34 are significantly different from zero for the U.S. Furthermore, the hypothesis that all intercepts are jointly zero would have to be rejected for all countries and both models. However, the GRS statistic for implied returns should be interpreted with caution as the assumption of independent and identically distributed regression residuals may be critical. Nevertheless, a huge improvement in the GRS statistic of the Fama-French model compared to the CAPM is observable.

Table 34: **Three-factor model regression of implied returns for the U.S.** The table reports the regression results of the Fama-French three-factor-model. Newey and West (1987) robust standard errors are used to adjust for autocorrelation and heteroskedasticity up to 12 lags. The regression R^2 and the residual standard error s(e) are adjusted for degrees of freedom. The statistics are computed over the period July 1990 to December 2011.

	Book-to-market equity (B/M)									
Size	Low	2	3	4	High	Low	2	3	4	High
	$R_{it} - RF_t = a_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + e_{it}$									
	a					$t(a)$				
Small	-0.09	0.02	-0.07	-0.07	-0.06	-1.12	0.65	-2.56	-3.57	-2.77
2	-0.04	-0.01	-0.03	-0.04	-0.06	-1.47	-0.46	-1.54	-2.44	-3.07
3	-0.05	-0.03	-0.04	-0.03	-0.01	-2.00	-1.72	-2.43	-1.46	-0.48
4	-0.06	-0.03	-0.01	-0.01	-0.06	-2.34	-1.61	-0.24	-0.30	-2.96
Big	-0.08	-0.05	-0.03	0.02	-0.04	-7.93	-3.08	-1.00	0.71	-1.07
	b					$t(b)$				
Small	1.14	1.00	1.11	1.07	1.03	11.73	14.36	29.21	44.52	36.95
2	1.08	0.99	1.00	0.98	1.05	20.04	38.33	31.91	48.46	28.42
3	0.93	0.99	0.98	0.97	0.97	26.10	39.80	33.00	26.07	21.50
4	0.95	0.94	0.90	0.94	1.02	27.22	24.21	19.54	23.37	33.36
Big	1.01	1.06	1.03	0.96	0.98	57.68	35.92	27.96	18.74	22.58
	s					$t(s)$				
Small	2.08	1.22	1.59	1.25	1.32	10.86	8.08	23.44	21.20	14.08
2	1.46	1.19	1.05	1.03	1.24	11.76	21.85	19.03	15.65	18.21
3	1.03	0.94	0.79	0.77	0.84	11.16	13.58	12.93	8.80	8.91
4	0.80	0.70	0.62	0.60	0.66	7.98	6.99	5.91	5.90	9.31
Big	0.09	0.25	-0.03	0.03	0.14	2.43	3.57	-0.31	0.29	1.35
	h					$t(h)$				
Small	0.17	0.07	0.24	0.63	1.04	0.67	0.42	2.82	12.62	14.38
2	-0.25	-0.06	0.28	0.61	0.93	-2.73	-1.00	4.05	11.38	8.55
3	-0.06	0.04	0.41	0.59	0.89	-0.77	0.79	5.78	5.59	10.73
4	-0.14	0.12	0.37	0.52	0.88	-1.70	1.16	3.04	5.40	16.16
Big	-0.17	0.02	0.38	0.49	1.07	-4.43	0.19	2.65	4.57	7.38
	R^2					$s(e)$				
Small	0.74	0.85	0.94	0.96	0.96	0.11	0.07	0.05	0.04	0.03
2	0.91	0.96	0.97	0.97	0.96	0.06	0.03	0.03	0.03	0.04
3	0.93	0.97	0.97	0.95	0.92	0.04	0.03	0.03	0.04	0.05
4	0.95	0.95	0.94	0.96	0.97	0.04	0.04	0.04	0.04	0.03
Big	0.99	0.98	0.96	0.96	0.95	0.02	0.03	0.05	0.04	0.05

Table 35: **Summary statistics for regressions in G-7 countries**
The table summarize the CAPM and Fama-French three-factor model regressions to explain excess returns on the 5×5 (4×4) size-B/M portfolios for the U.S. (other G-7 countries). I report the average adjusted coeffcient of determination R^2, the average absolute value of the intercepts $|\alpha|$, and the Gibbons et al. (1989) GRS statistic. In Panel A, I show statistics for my full sample, whereas in Panel B, I only use the subsample of realized returns for which also an implied return is available for the same month (I/B/E/S sample). In Panel C, I report the values for the implied returns of this subsample. The statistics are computed over the period July 1990 to December 2011.

Country	R^2	$\|\alpha\|$	GRS	R^2	$\|\alpha\|$	GRS
	CAPM			FF3FM		
Panel A: Realized returns of full sample						
US	0.54	0.34	4.17	0.80	0.23	3.92
JP	0.76	0.26	2.04	0.90	0.12	1.31
CN	0.59	0.17	1.08	0.77	0.13	0.87
UK	0.57	0.21	2.92	0.86	0.14	2.64
FR	0.60	0.23	1.37	0.81	0.15	1.14
BD	0.53	0.37	2.23	0.77	0.15	1.39
IT	0.68	0.28	2.12	0.79	0.26	2.39
Panel B: Realized returns of I/B/E/S sample						
US	0.63	0.33	1.86	0.88	0.18	1.70
JP	0.72	0.26	1.29	0.90	0.11	0.80
CN	0.54	0.23	0.93	0.73	0.19	0.88
UK	0.52	0.19	1.10	0.83	0.11	1.09
FR	0.58	0.21	1.59	0.81	0.14	1.42
BD	0.55	0.45	1.93	0.77	0.18	1.30
IT	0.63	0.32	1.47	0.77	0.23	1.19
Panel C: Implied returns of I/B/E/S sample						
US	0.81	0.21	168.38	0.94	0.04	25.36
JP	0.96	0.06	354.60	0.99	0.02	27.12
CN	0.81	0.10	86.59	0.88	0.06	6.92
UK	0.80	0.21	96.59	0.94	0.05	23.54
FR	0.81	0.17	213.45	0.93	0.06	56.96
BD	0.84	0.13	530.54	0.94	0.07	36.07
IT	0.89	0.12	159.69	0.92	0.05	12.84

5.6 robustness

As already mentioned in the introduction, the ICC is not without its own shortcomings. I will, therefore, address the most prominent points of criticism as well as their impact on my results.

5.6.1 *Different ICC estimates*

In this subsection, I re-run the analysis from the two previous sections with different ICC estimates. First, I compute the ICC with the GLS method but two different ROE proxies. Second, I calculate ICC with three alternative methods based on Claus and Thomas (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005).

5.6.1.1 *GLS based on target country ROE and actual EPS*

As described in Section 5.2, I linearly fade the forecasted three-year ahead ROE of a firm to a target industry ROE. I believe that this is a reasonable assumption: it appears likely that investors expect a firm to earn an industry ROE in the long run. Nevertheless, one could argue that instead of finding differences in expected returns, which I ultimately want to measure with the ICC approach, I only report differences in historical industry ROEs. This would occur in those cases in which the historical return between industries varies because of reasons that are unrelated to future developments. As an example, it could be that one industry has a high historical median ROE in comparison with other industries, but the ROE difference is not expected by investors to continue in the future. They consequently expect lower cash flows and hence lower returns than I compute. To address this issue, I re-run my analysis with a country ROE instead of an industry ROE. My results, as can be seen from Panel A of Table 36, are unchanged: both SMB and HML are still highly significant. This results in nearly identical alphas and R^2 for all countries, as Panel A of Table 37 shows.

Another issue often brought forward against the ICC methodology is that it relies on analyst forecasts, which tend to be systematically biased upwards, i.e., the actual earnings reported by firms are on average lower than those estimated by analysts.[85] However, note that analyst bias per se is not a problem for my analysis. First, my approach still yields the correct expected return estimate if analysts provide an unbiased estimator of investors' earnings expectation. Maybe investors are just as overly optimistic as analysts. Second, an analyst forecast bias is not a problem for my analysis as long as the bias is unrelated to the characteristics I study. Only if the bias is systematically higher for small and value firms, my results would be invalid because my findings would not indicate that investors expect higher returns for smaller firms and firms with a higher book-to-market ratio, but only that analyst forecasts of those firms are systematically biased upwards. To ensure that my results are not driven by an analyst bias, I replace their ex ante earnings estimates by the ex post realized earnings. Note, however, that this approach adds additional noise to the estimation of implied returns since realized earnings are the sum of expected earnings and an error term. Hence, I expect less significant results. Furthermore, this approach does not control for cash flow news anymore, which is one of the main advantages of the ICC methodology. Therefore, I strongly believe that that the ICC estimated with analyst forecasts are superior to those computed with realized earnings.

Panel B in Tables 36 and 37 shows the results based on ICC that are computed with actual earnings per share. The first interesting result is that the market premium is lower across all countries. Therefore, analysts overestimate the true earnings on average. Furthermore, the value premium is still significantly positive for all countries and around the same level. In contrast, the magnitude and the significance

85 For a summary of the analyst forecast literature see Ramnath et al. (2008).

of the size premium is lower: it is now only significant for three of the seven countries. Based on this evidence it seems that analysts are too optimistic, in particular for small firms. Nevertheless, the sign of the size premium is still positive for all countries except for the U.K. and Italy, where the premium is nearly zero. Despite the small differences for the risk premiums, the Fama-French three-factor model does a better job on explaining implied returns than the CAPM. For all countries the R^2 is rising and the average intercepts and GRS statistic are decreasing.

5.6.1.2 *Different ICC methods*

Finally, there is an ongoing debate on the preferred method to compute the ICC in the literature: while some authors discuss at length the pros and cons of the residual income model on a theoretical basis (e.g., Ohlson, 2005; Penman, 2005), others empirically compare the methods with actual data (see for example Guay et al., 2011; Botosan et al., 2011) and based on simulations (see Daske et al., 2010).[86] In my analysis, I focus on the GLS method because it is used as the main method by the studies most related to my work. Furthermore, Pástor et al. (2008) highlight that any reasonable measure of ICC should explain some of the time variation in expected returns. I can confirm this for the residual income model proposed by Claus and Thomas (2001, CT) in Panel A of Tables 38 and 39; however, while the evidence for the size premium is stronger, the magnitude and significance for the value premium is lower. In Panel B and C, I confirm the results of the GLS method for two derivatives of the abnormal earnings growth models: the implied cost of capital method based on Ohlson and Juettner-Nauroth (2005) and Gode and Mohanram (2003) (OJ) and the implied cost of capital method based on the modified price-earnings-growth ratio, proposed in Easton (2004, MPEG).[87]

86 Jäckel (2014) highlights that model uncertainty can be a problem when only one expected return proxy is applied. As an alternative, he proposes a Bayesian model averaging approach.

87 I thank Christoph Jäckel for providing the actual ICC data. Additional information on the ICC methodologies can be found in Hail and Leuz (2009), Jäckel and

5.6.2 *Industry portfolios as test portfolios*

Lewellen et al. (2010) are skeptical about the current standard of using only 25 (16) size and book-to-market portfolios and suggest to include other portfolios such as industry portfolios. Therefore, I apply my asset pricing tests on Industry Classification Benchmark (ICB) industry portfolios.[88] Panel A of Table 40 displays my results for realized returns. For the CAPM, the level of the R^2 and average intercepts is similar to the size and book-to-market portfolios, but adding SMB and HML does not improve the average intercepts and GRS statistic as much as for the standard Fama-French portfolios. Fama and French (2012) mention that time-varying slopes on the industry portfolios as in Fama and French (1997) could be a problem for tests on these portfolios.

Keeping this in mind, the results for implied returns in Panel B are better. The already high R^2 are still rising when I add the size and book-to-market factors to the CAPM. Although I observe little or no improvement in the average intercepts, I observe a considerable improvement in the GRS statistic for the Fama-French three factor model for all countries except France. On that score and as the intercepts do not exceed 0.1% per month for the implied returns I do not reject my statement that the Fama-French three-factor model does a better job for implied returns than the standard capital asset pricing model.

Mühlhäuser (2011) and Jäckel et al. (2013). I refer the interested reader to their studies for implementation details.

88 I use ICB industry classification instead of SIC classification as the coverage for ICB is better than for SIC in Datastream.

Table 36: **Robustness risk factors - Target country ROE and actual EPS**
The table reports summary statistics of the market return (RM), the risk free rate (RF), the excess return of the market over the risk free rate (RMRF = RM − RF), the size factor (SMB), and the value factor (HML) for the G-7 countries. The panels show the implied return risk premiums for different calculation methods. More precisely, Panel A shows the results for a GLS method where a country median, and not an industry median, is used as a long-term target ROE. Panel B is computed with actual earnings per share instead of forecasted ones. For implied returns, t-statistics are based on Newey and West (1987) robust standard errors to adjust for autocorrelation and heteroskedasticity up to 12 lags. The statistics in Panel A are computed over the period July 1990 to December 2011. For the actual earnings in Panel B the statistics are computed over the period July 1990 to June 2010. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Country	RM	[t]	RF	[t]	RMRF	[t]	SMB	[t]	HML	[t]
Panel A: GLS country										
US	0.67***	36.02	0.28***	25.91	0.39***	8.89	0.08***	6.44	0.24***	18.63
JP	0.40***	12.69	0.11***	9.86	0.29***	5.51	0.06***	5.17	0.19***	21.14
CN	0.72***	39.55	0.35***	28.34	0.37***	9.07	0.12***	8.14	0.19***	10.49
UK	0.85***	29.16	0.45***	30.45	0.40***	7.18	0.15***	8.36	0.33***	21.14
FR	0.75***	22.50	0.35***	24.10	0.40***	7.67	0.09***	6.18	0.32***	21.31
BD	0.63***	19.25	0.33***	26.64	0.31***	4.71	0.11***	5.74	0.29***	23.35
IT	0.62***	14.91	0.44***	22.80	0.18**	2.25	0.06***	4.16	0.31***	15.71
Panel B: GLS actual EPS										
US	0.62***	24.80	0.30***	28.77	0.32***	6.28	0.02	1.51	0.26***	14.70
JP	0.34***	11.57	0.11***	9.89	0.23***	4.22	0.06***	5.21	0.17***	20.35
CN	0.67***	39.77	0.37***	29.87	0.31***	6.63	0.00	0.02	0.26***	18.51
UK	0.83***	23.23	0.48***	34.03	0.35***	6.17	-0.00	-0.12	0.32***	5.64
FR	0.69***	21.89	0.37***	25.04	0.32***	5.44	0.05***	4.30	0.31***	12.86
BD	0.58***	16.12	0.34***	27.91	0.23***	3.30	0.04**	1.99	0.27***	16.63
IT	0.59***	16.73	0.46***	23.75	0.13	1.57	-0.00	-0.00	0.23***	11.00

Table 37: **Robustness summary statistics for regressions - Target country ROE and actual EPS**
The table summarizes the CAPM and Fama-French three-factor model regressions to explain excess returns on the 5×5 (4×4) size-B/M portfolios for the U.S. (other G-7 countries). I report the average adjusted coeffcient of determination R^2, the average absolute value of the intercepts $|\alpha|$, and the Gibbons et al. (1989) GRS statistic. Panel A shows the results when a country median, and not an industry median, is used. The results in Panel B are based on ICC computed on actual earnings per share, not on forecasted ones. The statistics in Panel A are computed over the period July 1990 to December 2011. For the actual earnings in Panel B the statistics are computed over the period July 1990 to June 2010.

Country	R^2	$\|\alpha\|$	GRS	R^2	$\|\alpha\|$	GRS
	CAPM			FF3FM		
Panel A: GLS country						
US	0.82	0.21	223.32	0.94	0.04	31.79
JP	0.95	0.07	295.68	0.99	0.03	22.91
CN	0.81	0.11	105.06	0.89	0.06	15.99
UK	0.84	0.18	179.33	0.95	0.09	29.72
FR	0.86	0.16	236.79	0.94	0.07	34.35
BD	0.88	0.12	666.90	0.95	0.08	39.89
IT	0.90	0.13	276.47	0.93	0.05	13.23
Panel B: GLS actual EPS						
US	0.82	0.14	178.28	0.94	0.03	19.97
JP	0.96	0.06	326.62	0.99	0.04	34.44
CN	0.76	0.08	67.64	0.84	0.05	19.97
UK	0.56	0.13	69.47	0.81	0.06	41.69
FR	0.83	0.12	191.32	0.91	0.07	50.21
BD	0.83	0.11	215.11	0.90	0.07	13.59
IT	0.85	0.09	322.83	0.88	0.06	63.57

Table 38: **Robustness risk factors - Different ICC methods**
The table reports summary statistics of the market return (RM), the risk free rate (RF), the excess return of the market over the risk free rate (RMRF = RM − RF), the size factor (SMB), and the value factor (HML) for the G-7 countries. The panels show the implied return risk premiums for different calculation methods. More precisely, Panel A shows the results for the residual income model proposed by Claus and Thomas (2001, CT). Panel B and C are computed with implied returns based on two abnormal earnings growth models: the implied cost of capital method based on Ohlson and Juettner-Nauroth (2005) and Gode and Mohanram (2003) (OJ) and the implied cost of capital method based on the modified price-earnings-growth ratio, proposed in Easton (2004, MPEG). For implied returns, t-statistics are based on Newey and West (1987) robust standard errors to adjust for autocorrelation and heteroskedasticity up to 12 lags. The statistics are computed over the period July 1990 to December 2011. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Country	RM	[t]	RF	[t]	RMRF	[t]	SMB	[t]	HML	[t]
					Panel A: CT					
US	0.73***	34.20	0.28***	25.91	0.45***	12.58	0.09***	6.52	0.06***	6.29
JP	0.50***	18.32	0.11***	9.86	0.39***	7.67	0.17***	7.00	0.06***	3.99
CN	0.86***	29.77	0.35***	28.34	0.51***	17.62	0.28***	9.37	0.07**	2.57
UK	0.81***	31.58	0.45***	30.45	0.36***	7.98	0.33***	17.21	0.03	1.47
FR	0.75***	30.95	0.35***	24.10	0.40***	8.69	0.19***	9.27	0.16***	8.66
BD	0.70***	32.12	0.33***	26.64	0.38***	7.78	0.26***	7.54	0.13***	8.90
IT	0.79***	22.73	0.42***	22.18	0.37***	6.08	0.21***	8.47	0.15***	5.10
					Panel B: OJ					
US	0.85***	45.22	0.28***	25.91	0.58***	15.61	0.13***	10.94	0.07***	6.03
JP	0.67***	20.46	0.11***	9.86	0.56***	9.59	0.13***	6.76	0.08***	4.81
CN	1.02***	35.23	0.35***	28.34	0.68***	20.07	0.25***	8.36	0.10***	3.41
UK	0.91***	34.85	0.45***	30.45	0.46***	9.66	0.29***	13.84	0.10***	4.17
FR	0.88***	42.85	0.35***	24.10	0.53***	11.15	0.19***	11.13	0.20***	10.05
BD	0.85***	37.45	0.33***	26.64	0.52***	9.53	0.28***	8.59	0.17***	7.84
IT	0.91***	34.85	0.45***	30.45	0.46***	9.66	0.29***	13.84	0.10***	4.17
					Panel C: MPEG					
US	0.84***	42.91	0.28***	25.91	0.57***	13.02	0.15***	11.75	0.14***	8.14
JP	0.68***	17.76	0.11***	9.86	0.58***	8.58	0.11***	5.62	0.10***	5.67
CN	0.97***	41.50	0.35***	28.34	0.63***	16.05	0.27***	7.48	0.13***	3.77
UK	0.88***	37.56	0.45***	30.45	0.43***	7.83	0.28***	12.06	0.12***	4.33
FR	0.87***	37.73	0.35***	24.10	0.52***	9.47	0.19***	8.13	0.26***	10.60
BD	0.85***	25.71	0.33***	26.64	0.53***	7.92	0.26***	8.13	0.22***	8.99
IT	0.88***	37.56	0.45***	30.45	0.43***	7.83	0.28***	12.06	0.12***	4.33

Table 39: **Robustness summary statistics for regressions - Different ICC methods**
The table summarizes the CAPM and Fama-French three-factor model regressions to explain excess returns on the 5×5 (4×4) size-B/M portfolios for the U.S. (other G-7 countries). I report the average adjusted coeffcient of determination R^2, the average absolute value of the intercepts $|\alpha|$, and the Gibbons et al. (1989) GRS statistic. Panel A shows the results for the residual income model proposed by Claus and Thomas (2001, CT). Panel B and C are computed with implied returns based on two abnormal earnings growth models: the implied cost of capital method based on Ohlson and Juettner-Nauroth (2005) and Gode and Mohanram (2003) (OJ) and the implied cost of capital method based on the modified price-earnings-growth ratio, proposed in Easton (2004, MPEG). The statistics are computed over the period July 1990 to December 2011.

Country	R^2	$\lvert\alpha\rvert$	GRS	R^2	$\lvert\alpha\rvert$	GRS
	CAPM			FF3FM		
			Panel A: CT			
US	0.76	0.19	67.62	0.90	0.03	19.16
JP	0.88	0.04	18.99	0.96	0.02	14.36
CN	0.42	0.25	25.72	0.67	0.11	12.05
UK	0.75	0.24	107.18	0.88	0.08	15.83
FR	0.71	0.18	52.61	0.84	0.06	18.38
BD	0.69	0.15	159.84	0.86	0.05	89.55
IT	0.59	0.22	53.55	0.68	0.08	12.31
			Panel B: OJ			
US	0.78	0.23	53.83	0.90	0.03	8.36
JP	0.90	0.03	11.91	0.96	0.02	7.92
CN	0.46	0.27	19.28	0.71	0.11	11.93
UK	0.75	0.26	84.96	0.89	0.06	12.37
FR	0.75	0.17	45.62	0.85	0.07	14.81
BD	0.76	0.12	47.14	0.88	0.05	29.18
IT	0.75	0.26	84.96	0.89	0.06	12.37
			Panel C: MPEG			
US	0.76	0.26	47.98	0.89	0.04	5.76
JP	0.91	0.04	17.86	0.96	0.03	10.85
CN	0.56	0.16	16.28	0.77	0.08	9.74
UK	0.80	0.22	65.13	0.91	0.07	12.66
FR	0.76	0.17	42.03	0.88	0.05	14.12
BD	0.80	0.11	45.54	0.88	0.05	20.13
IT	0.80	0.22	65.13	0.91	0.07	12.66

Table 40: **Robustness summary statistics for regressions - Industry portfolios**

The table summarizes the CAPM and Fama-French three-factor model regressions to explain excess returns on industry portfolios for the U.S. (other G-7 countries). I report the average adjusted coeffcient of determination R^2, the average absolute value of the intercepts $|\alpha|$, and the Gibbons et al. (1989) GRS statistic. Panel A shows the regression results on industry portfolios based on realized returns, whereas in Panel B, I report the statistics for implied returns. The statistics are computed over the period July 1990 to December 2011.

Country	R^2	$\|\alpha\|$	GRS	R^2	$\|\alpha\|$	GRS
	CAPM			FF3FM		
Panel A: Industry portfolios on realized returns						
US	0.56	0.13	1.23	0.62	0.20	1.70
JP	0.64	0.17	4.97	0.67	0.26	3.66
CN	0.40	0.24	1.78	0.44	0.27	1.65
UK	0.50	0.24	3.62	0.56	0.27	3.59
FR	0.58	0.26	2.95	0.62	0.25	1.99
BD	0.58	0.41	2.34	0.62	0.50	2.43
IT	0.56	0.38	1.30	0.62	0.32	1.05
Panel B: Industry portfolios on implied returns						
US	0.90	0.10	277.52	0.92	0.06	43.46
JP	0.95	0.03	216.38	0.95	0.04	42.53
CN	0.82	0.10	122.73	0.85	0.08	30.87
UK	0.81	0.16	210.63	0.85	0.10	62.80
FR	0.88	0.08	39.33	0.91	0.10	76.63
BD	0.86	0.09	488.04	0.88	0.06	43.00
IT	0.89	0.10	292.03	0.91	0.09	85.74

5.7 IMPLICATIONS

In this section, I discuss the implications my results have on the ongoing debate about the source of the size and value factor returns.[89] Fama and French (1996) identify three main arguments of the explanatory power of the size and value factors. The first explanation is that the returns of SMB and HML are indeed premiums associated with additional risk which is not part of beta. Consequently, the CAPM has to be discarded and replaced by a multifactor model that includes SMB and HML. Second, the market is not efficient and the profits are the result of systematic mispricing. Or third, the empirical evidence is spurious because of survivorship bias or simply data mining.

My evidence contradicts the last argument. The analysis in this chapter provides counter evidence against those studies that identify data issues such as survivorship and data snooping as the main drivers of the significant loadings on SMB and HML in empirical analysis. I use a completely different proxy for expected returns and apply this proxy to a large international dataset ranging up to December 2011 and still find significant SMB and HML premiums. It is hard to argue that the evidence based on both realized and implied returns is all due to spurious data. However, one could object that the use of biased analyst forecasts introduces systematic errors that drive my results, but do not drive true return expectations by market participants. Based on my results using actual earnings in Table 36, analyst forecast bias appears not to be the reason for the implied value premium as it is about the same as the one with analyst forecasts. Maybe analyst forecast bias is a bigger problem for the size premium. In all seven countries, the implied SMB estimate with actual earnings is lower than that for the estimate based on analyst forecasts. Nevertheless, the premium is still positive and significant in four out of seven

89 For example, van Dijk (2011) is an excellent recent review of the literature on the size effect. Also, several studies in the last years focus on the value premium, such as Zhang (2005), Petkova and Zhang (2005), and Lettau and Wachter (2007).

countries and it is just a little bit lower than expected with analyst forecasts. This would be consistent with recent evidence that the realized size premium is smaller over longer horizons than estimated in Fama and French (1993).[90]

This leaves us with two reasons why the implied premiums for the size and value factors are positive: mispricing and risk.[91] The former implies that the market prices for value (small) stocks are too low compared with growth (big) stocks. Thus, the analyst earnings expectations are right, but the market price determined by the marginal investor is wrong that corresponds to mispricing. The latter implies that value (small) stocks are riskier than growth (big) stocks and must offer a higher expected return.

First, I discuss the mispricing story. Maybe a part of this mispricing disappears when new information arrives at the market with earnings announcements. If risk plays a minor role in short time windows, higher cumulative abnormal returns (CARs) around these earnings announcements days for value (small) stocks than for growth (big) stocks would indicate mispricing. Porta et al. (1997) report this evidence for value stocks. Li et al. (2014) extend this analysis and show that differences in CARs of the value factor can be explained by the ex ante expected value premium and summarize that there is an important mispricing component in the expected value premium. However, I believe that also risk can explain these higher CARs if the risk (uncertainty) associated with the announcement drops for HML around the announcement and as a consequence realized returns are positive.

Within the risk story, investors expect higher premiums for both smaller and value firms in the long term as they consider them as riskier. According to Tang et al. (2014), average realized returns equal average expected returns plus average unexpected returns. If mispricing due to investor irrationality plays a minor role, average expected and realized returns should be the same. Figure 7 and Figure 8 show

90 See, e.g., van Dijk (2011).
91 Of course also combinations of the reasons offered could be an explanation.

Figure 7: **Time-series characteristics of implied market, size, and value premiums for the U.S.**
The figure plots the monthly time-series of the annualized market (RMRF), size (SMB), and value (HML) premiums for the U.S. All factors are computed with implied risk premiums. The statistics are computed over the period from 1990 to 2011.

Figure 8: **Time-series characteristics of implied market, size, and value premiums outside the U.S.**
Each panel plots the monthly time-series of the annualized market (RMRF), size (SMB), and value (HML) premiums for the given country. All factors are computed with implied risk premiums. The statistics are computed over the period from 1990 to 2011.

the market, size, and value premium over time for the U.S and the other G-7 countries, respectively. If implied returns are a good proxy for return expectations and if SMB and HML are risk factors, they should be positive throughout the observation period. By and large, this is what I observe. Both SMB and HML are almost always positive across the seven countries and over time. Furthermore, the theoretically most grounded risk factor, the market risk premium, is the only one that has relevant periods in which it is negative. This, however, only occurs at the beginning of my sample period, a period which faces some data issues.[92] Thus, in summary, I favor the risk-based story of the size and value factors.

92 The I/B/E/S coverage is very low at the beginning of my sample and it is also likely that the quality of the data base increased over time. Additionally, the interbank rates for Italy were very high at the beginning of the 90s, questioning their suitability as a risk-free rate proxy.

5.8 summary

This chapter tests the validity of the Fama-French three-factor model in an international setting and with an alternative estimate of expected returns - the implied cost of capital (ICC).

I find that implied returns give much more precise estimators for the risk premiums compared with realized risk premiums, because they are both highly significant and fairly homogeneous across countries. This is in line with the argument that risk premiums between developed countries should not vary much due to the possibility of investors to diversify internationally. According to my data, risk premiums of 3% to 5% per year for the market, of 1% to 2% for the size factor, and of 2% to 3% for the value factor appear reasonable.

Furthermore, I show that the identified risk factors do a very good job in explaining the cross-section of average implied stock returns. The regressions based on sorts of size and book-to-market show highly significant loadings for the size (value) factor that are monotonically decreasing (increasing) with size (book-to-market). This produces very high R^2 (>0.92 for all countries except Canada) that leaves little variation for other factors. Merton (1973) and Fama and French (1993) note that for a well-specified asset pricing model the intercepts should be indistinguishable from zero. Although portfolio intercepts for the three-factor model display significant alphas, I observe a huge improvement for the GRS statistic compared to the CAPM. Furthermore, the average intercepts are close to zero (smaller than 1% per year for all countries), and hence economically not considerable. Thus, I conclude that the Fama-French three-factor model is an appropriate asset pricing model using ICC, an alternative expected return proxy.

However, my approach is not without its own limitations. To start with, the inclusion of a firm is dependent on the coverage of I/B/E/S, which biases my sample toward larger firms and leads to portfolios with few observations, particularly at the beginning of my sample and for Italy, the smallest country in my dataset. However, I show that the factors based on realized returns only differ slightly between the full sample and the sample of firms with I/B/E/S coverage. Also, a critique that is often brought forward against the ICC approach is that it heavily relies on analyst forecasts, which may not be an unbiased estimator of investors' expectations. To address this critique, I show that my main results still hold when I replace the forecasts by subsequent actual earnings.

My results should be of interest to researchers and practitioners alike. I enrich the ongoing debate about the merits of the Fama-French three-factor model with empirical evidence that is confirmative for the model. In a nutshell, my analysis supports the application of the model in event studies, performance evaluation, and the cost of capital estimation. For the latter, however, I propose the use of implied instead of realized returns.

6 CONCLUSION

6.1 SUMMARY

Fama and French (1993) add two additional return factors to the CAPM to explain the cross-section of stock returns. The two factors, SMB and HML, are zero-cost portfolios related to size and book-to-market. The resulting so-called Fama-French three-factor model captures cross-sectional patterns in portfolios sorted by size and book-to-market better than the CAPM. Furthermore, the three-factor model was also able to explain return differences associated with other characteristics, such as price-earnings ratio, price-cash flow-ratio, past sales growth, and long-term past return, as demonstrated in Fama and French (1996). Only the continuation of medium-term past returns, discovered by Jegadeesh and Titman (1993), could not be captured. Therefore, Carhart (1997) extends the model by another factor, WML, related to the medium-term past performance of common stocks, to account for the differences in average returns from winner stocks to loser stocks. The high explanatory power for different sorting schemes is the reason why the Fama-French three-factor and Carhart four-factor models still constitute the "industry standard" (Subrahmanyam, 2010, p. 35) in empirical asset pricing.

Fama and French (1996) identify three main arguments for the explanatory power of the two additional factors in the Fama-French three-factor model. The first explanation is that the factors related to size and book-to-market are proxies for additional risk factors not captured by the CAPM. The second explanation accepts the higher explanatory power of the multifactor model, but argues that mispricing and not risk leads to the rejection of the CAPM. The third explanation in Fama and French (1996) is that the empirical evidence is spurious because of survivorship bias, bad proxies for the market portfolio, or simply data snooping.

Data snooping means that, ex post, one always finds some deviations from the CAPM by dredging up a given dataset.[93] By grouping these observations into portfolios, the deviations appear statistically significant; however, only because the disturbances and sorting criteria are correlated.[94] Consequently, repeated tests on nearly the same data samples and the same data treating conventions lead to the same results. Therefore, out-of-sample tests are needed to rebut the data snooping criticism.

Schwert (2003) highlights that "the key test is whether the anomaly persists in new, independent samples" (p. 941). Persistence in younger data samples is important, as there are two explanations for why anomalies that previously existed could disappear after their documentation; beside data snooping, these opportunities could be arbitraged away by investors trying to harvest the documented "abnormal" returns. Therefore, new and younger samples have the additional advantage of testing whether the anomalies lived on in periods that are more recent. Consequently, this dissertation focuses on two samples previously less researched than others, and on one observation that is regarded as an empirical failure of one of the three big anomalies, momentum returns in Japan.

Chapter 2 presents details about the sample definition, data quality screens, and portfolio construction using Thomson Reuters Datastream (TRD) as the data source for my out-of-sample tests. Assuring data quality is essential when using data from TRD, as Ince and Porter (2006) emphasize that raw return data from TRD may not be error-free. I describe the steps to obtain a sample free from survivorship bias including static and dynamic data quality screens. Furthermore, I detail the different breakpoint approaches within the liter-

93 See MacKinlay (1995).
94 See Lo and MacKinlay (1990).

ature and their effects on the distribution of the aggregated market capitalization over the portfolios needed to calculate the Fama-French factors. Finally, I provide evidence that these steps lead to comparable results for U.S. and international risk factors derived from TRD and the ones provided by Kenneth French's data library that are constructed as in Fama and French (1993) and Fama and French (2012).

Studies analyzing developed markets outside the U.S. mainly confirm the size, value, and momentum patterns found for the U.S. for similar periods. However, under the hypothesis that developed markets are integrated, the same risk factors should apply to these markets. Hence similar results for similar periods are not surprising. Samples out of emerging market stocks provide an attractive alternative for out-of-sample tests in terms of independent and new samples compared to developed markets samples. In contrast to developed markets, few have investigated emerging markets, although the importance of emerging market economies and stock markets is constantly rising.[95] Therefore, I provide a detailed analysis for a broad set of emerging market countries in a methodologically consistent way in Chapter 3.

Examining emerging market stock returns in Chapter 3 is threefold. First, I determine the magnitude of standard risk factors based on a broad sample of stocks from 21 emerging market countries. Second, I explore size patterns in value and momentum returns of emerging market stock returns. Third, I discuss market integration with a clear focus on Emerging Markets (comprising all 21 emerging market countries) and four emerging market regions (EM Latin America, EM EMEA, EM Asia, and BRIC).

My analysis leads to three major results. First, I find a strong and highly significant value effect, as well as a strong but less significant momentum effect in emerging markets and all emerging market regions. The size factor is less pronounced and is only significant in

95 The Organization for Economic Co-operation and Development (OECD) estimates a dramatic change in the relative size of economies within the next 50 years, a shift toward emerging countries (Johansson et al., 2012).

emerging Asian markets and BRIC. Second, I provide evidence of value and momentum spreads for different size groups. I cannot document smaller value spreads for bigger stocks as seen in Fama and French (2012) for developed markets. Furthermore, I get mixed results for momentum spreads. Third, I have to reject integrated global pricing for all of my emerging markets samples. Nevertheless, local models with local risk factors fit well, and the local four-factor models, in particular, are appropriate asset pricing models to explain stock returns in emerging markets.

In general, as for developed markets in Fama and French (2012), my models face more problems in explaining size-momentum portfolio returns than in explaining size-value portfolio returns. For size-value portfolios, there is only a marginal difference between the results of the three-factor model and the four-factor model. Thus, if a portfolio without momentum tilts should be priced, the three-factor model is sufficient for accurate pricing. Adding WML is not necessary but does not harm the results. However, the four-factor model is superior when applied to size-momentum portfolios. Microcaps in emerging markets are not as challenging for the models as in developed markets. Only for the size-momentum portfolios in Emerging Markets and for both portfolio sorts in EM Latin America, the models perform significantly better if microcaps are excluded. In sum, local four-factor models are the right choice for pricing diversified emerging market portfolios.

In Chapter 4, I investigate a fact generally referred to as an empirical failure of one of the big three anomalies, momentum. Despite the broad evidence of momentum profits around the world, there is one remarkable exception. Several studies argue that momentum strategies fail in Japan as they do not find any significant premium or even observe a negative mean return.

In contrast to the majority of studies on momentum, I focus on momentum profits under different market dynamics. According to the behavioral model of Daniel et al. (1998), investors' overconfidence is expected to be higher when the market remains in the same state than when it reverses. Therefore, momentum returns should be higher in market continuations than in market transitions. Asem and Tian (2010) provide mixed evidence; because they can present this pattern for the U.S. but not for Japan.

I instead show that market-dynamic conditional momentum is also present in the Japanese stock market by examining a comprehensive and carefully screened dataset. I observe that momentum returns are significantly higher when the market stays in the same condition than when it transitions to the other state. Furthermore, this pattern is more pronounced after periods of poor market performance. A potential explanation for this contrast might be the result of the option-like payoff of the loser portfolio after market declines. However, the question of why momentum on average exhibits no significant premium remains. Assuming that the distribution of market transitions for Japan is the same as in the U.S., the magnitude of momentum premiums would be substantially higher. Overall, my findings indicate that different market dynamics, and not different momentum, cause the overall low momentum returns in Japan. Finally, my results are robust under various specifications, and also hold for other countries with low average momentum returns.

My findings contribute to the existing literature in at least two ways. To the best of my knowledge, I am the first to provide evidence outside the U.S. that momentum returns are conditional on market dynamics. Moreover, my findings explain why average momentum returns have historically been low in Japan, a fact generally referred to as an empirical failure of momentum.

Chapter 5 focuses on expected returns, as asset pricing models typically build on expected returns. Consequently, to test the empirical validity of an asset pricing model, one first must find a reasonable proxy for expected returns. Due to the difficulties in observing expectations, realized returns are thus far the most common proxy in empirical studies; to the best of my knowledge, the explanatory power of the Fama-French three-factor model has only been evaluated using realized returns. However, I am the first to validate the Fama-French three-factor model utilizing implied cost of capital (ICC). Thus, my main contribution is providing evidence about the appropriate asset pricing model using an alternative expected return proxy. In other words, I test the validity of the Fama-French three-factor model in an international setting and with an alternative estimate of expected returns - the ICC.

I find that implied returns give much more precise estimators for the three factor risk premiums compared with realized risk premiums, because they are both highly significant and also fairly homogeneous across countries. This is in line with the argument that risk premiums between developed countries should not vary much due to the possibility of investors to diversify internationally.

Furthermore, I show that the identified risk factors, and therefore the Fama-French three-factor model do a very good job in explaining the cross-section of average implied stock returns. The regressions based on sorts of size and book-to-market show highly significant loadings for the size and value factors, and the explanatory power of the model is higher compared to the CAPM. Merton (1973) and Fama and French (1993) note, that for a well-specified asset pricing model, the intercepts should be indistinguishable from zero. Although portfolio intercepts for the three-factor model display significant alphas, I observe a huge improvement for the GRS statistic compared to the CAPM. Furthermore, the average intercepts are close to zero, and hence economically not considerable. Thus, I conclude that the Fama-French three-factor model also is an appropriate asset pricing model using ICC, an alternative expected return proxy.

In sum, the individual chapters of this thesis document that it is very unlikely that data snooping drives the explanatory power of the extended versions of the CAPM. First, I demonstrate that comparable risk factors can be constructed using an alternative data provider, Thomson Reuters. Second, I show that value and momentum patterns also are present in emerging markets, a new and independent test sample. Within emerging markets, local multifactor models do a better job than global models or the local CAPM in explaining the cross-section in emerging markets returns. Third, I explain why average momentum returns have historically been low in Japan, a fact generally referred to as an empirical failure of momentum. My findings indicate that different market dynamics, and not different momentum, cause the overall low momentum returns in Japan. Finally, I provide evidence that size and value patterns also are present in implied stock returns, and that the Fama-French three-factor model does a better job in explaining these patterns than does the CAPM. Overall, the results in this thesis suggest that the probability that data snooping is driving the results is very low due to the evidence in old as well as in new and independent samples.

6.2 IMPLICATIONS

The results presented in this thesis have several implications and should be of interest to researchers and practitioners alike. The Fama-French three-factor and Carhart four-factor models justly remain the industry standard in empirical asset pricing. My analysis supports the application of the model in estimating the cost of capital, evaluating portfolio performance, or measuring abnormal returns in event studies.

For estimating the cost of capital of a firm's securities or a portfolio, Fama and French (1993) propose a regression of past returns on the risk factors. The estimated regression slopes represent the firm's or portfolio's exposures toward the risk factors. Historical average returns provide proxies for expected risk factor premiums. Together with the regression slopes, the expected risk factor premiums can be used to estimate the expected return of the firm or portfolio. However, long time-series data to calculate statistically robust proxies for the expected risk factor premiums might be hard to obtain outside the U.S. Implied risk premiums as calculated in Chapter 5 offer an interesting alternative. According to my data, risk premiums of 3% to 5% per year for the market, of 1% to 2% for the size factor, SMB, and of 2% to 3% for the value factor, HML, appear reasonable for developed markets. Adding the momentum factor to the model to estimate the cost of capital seems unnecessary, because the momentum effect is rather short-lived.[96]

For other purposes, adding momentum seems more reasonable. Besides measuring abnormal returns in long-term event studies, performance evaluation and investment management are areas for application.[97] According to Carhart (1997), the momentum factor helps to explain the cross-section of mutual funds' performance. While fund rating agencies, such as Morningstar, classify funds into size and value-growth boxes, classifications by momentum style are not common.[98] However, Ang et al. (2009a) highlight the importance of factors for explaining the returns of actively managed funds, such as the Norwegian Government Pension Fund, and recommend including factors such as size, value, momentum, and volatility in the benchmarks of mutual funds.[99] The advanced benchmarks should aid in better understanding the risk-return trade-off and raise the bar for active management.

Chapter 4 describes the risks and returns of momentum strategies in Japan. My findings explain why average momentum returns have historically been low, a fact generally referred to as an empirical failure of momentum. Furthermore, my results help to understand the returns and risks of momentum strategies in general. Investors should be aware that momentum strategies might be exposed to sharp drawdowns following periods of poor market performance contemporaneous with recovering markets. On the other hand, this risk is rewarded

96 See Fama and French (2004).
97 See, e.g., Fama and French (2010) or Fischer et al. (2013).
98 See Morningstar Inc. (2008).
99 Initial steps toward such benchmarks are factor indices, e.g., calculated by MSCI (see MSCI Inc., 2012b, 2013).

by high average momentum profits if the market remains in the same condition. As documented in Subsection 4.5.2, this risk stems primarily from the short leg of the strategy. Hence, investors investing only in the long leg of the strategy may not be exposed to the sharp drawdowns described above. However, investors who are interested in a long-short momentum strategy or concerned about returns relative to the market may consider the residual momentum strategy, a modified momentum strategy proposed by Blitz et al. (2011).

To conclude, this thesis provided further insight on multifactor models, such as the Fama-French three-factor and the Carhart four-factor models, and their associated risk factors. Besides the evidence on previously less researched samples, the results should motivate the implementation of such models to address financial questions.

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