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Investments in Emerging Markets: Alpha and The Benefits of Active Portfolio Management

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Abstract

In this thesis, I investigate whether investments in emerging market stocks can generate a higher risk-adjusted portfolio return than investments in developed markets. To investigate the possibilities of abnormal performances, I use stock indices representing emerging markets in the period of January 2001 to December 2014.

My underlying hypothesis is set in context with active- and passive portfolio allocation. By backtesting my assumed active portfolio strategies, I can obtain adequate number of test results to answer my underlying hypothesis. The active emerging market portfolio strategies are the Maximum Sharpe portfolio and the Minimum Variance portfolio. In order to see the risk-return effects, I chose the MSCI World index as benchmark index. Moreover, I use the information rate as a measure of active management success.

The success of an active portfolio strategy hinges on the existence of alpha. In order to find evidence of its existence, I dedicate my second analysis to cover asset-pricing models. I base my analysis on the three-factor model of Fama and French (1993). I experiment with my backtested portfolios and a dataset covering style stocks from the BRICS.

I found that the active emerging market portfolios did not generate a higher risk-adjusted return than the benchmark index. On an unadjusted basis, the Minimum Variance portfolio performed best. The multifactor asset-pricing models indicated a size premium on this portfolio that explained some of the performance.

I also found significant size- and value premiums of the BRICS style portfolios. The multifactor asset-pricing models provided evidence of the shortcomings of the CAPM. Specifically, small stocks seem to have return patterns in which the market beta lack the ability to explain.

Based on my findings, I suggest that passive replication strategies can generate just as high returns as active portfolio strategies by reaping premiums of risky stocks. For future research, I encourage further investigation of the size and value anomalies within emerging market stocks.

Sammendrag

I denne avhandlingen undersøker jeg hvorvidt investeringer i aksjer representert fra vekstmarkeder kan generere høyere risikojustert avkastning enn ved investeringer i utviklede markeder. For å undersøke mulighetene hvorvidt dette er mulig, benytter jeg meg av aksjeindekser fra vekstmarkeder i perioden januar 2001 – desember 2014.

Jeg setter hypotesen i sammenheng med aktiv- og passiv porteføljeforvaltning. Ved å «back-teste» mine antatte aktive porteføljestrategier oppnår jeg tilstrekkelig med prøve-resultat til å kunne teste min underliggende hypotese. Disse porteføljene er Maximum Sharpe porteføljen og Minimum Varians porteføljen. For å kunne se porteføljenes risiko-avkastningsforhold har jeg valgt MSCI World indeksen som referanse indeks. For å kunne teste dette forholdet har jeg valgt informasjonsraten som mål på suksess.

Suksessen til en aktive porteføljeforvalter avhenger av om en har ferdigheter til å generere alfa. For å kunne analysere om mine porteføljer har oppnådd dette, dedikerer jeg mitt andre analyse kapittel til å omhandle pris-modeller. I denne analysen baserer jeg meg på tre-faktor modellen til Fama and French (1993). Jeg eksperimenterer med mine testede porteføljer og et nytt datasett som omfavner aksjer med ulik markedsstørrelse, verdiaksjer og vekstaksjer fra BRICS landene.

I analysen fant jeg at mine vekstmarkedsporteføljer ikke klarte å generere høyere risikojustert avkastning enn referanseindeksen. Jeg fant derimot at Minimum Varians porteføljen presterte best, men at dette til dels kunne tilskrives høsting av risikopremier.

Videre i analysen fant jeg både størrelses- og verdipremier for de forskjellige BRICS porteføljene. Mine to flerfaktormodeller avslørte dermed CAPM's svakheter. Mer spesifikt, avkastningsmønstre til aksjer i selskaper med liten markedsstørrelse viste seg å være vanskelig for markedsfaktoren å forklare.

Basert på mine funn, er det lettere å anbefale passive replikasjonsstrategier fordi man har mulighet til å generere like høy avkastning ved å høste risikopremier. For fremtidig forskning oppmuntrer jeg til å studere størrelses- og verdieffektene i aksjer fra vekstmarkeder videre.

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1. Introduction and problem formulation

Trade liberalization has opened up the opportunity set for investors worldwide. Due to barriers facing individual investors in an international context, they may choose a fund manager to manage their money to obtain the desired level of exposure. Maybe the most difficult part is to combine your own preferences with the appropriate fund. Today, the ongoing debate whether to follow an active- or passive investment strategy and which is most beneficial, does not make the decision easier.

In this context, I wanted to investigate the benefits of active investments within emerging market (EM) stocks. My underlying hypothesis is that investments in EM stocks can generate a higher risk-adjusted portfolio return than investments in developed market (DM) stocks. By applying a backtest of my theoretical motivated portfolios, I can answer the underlying research question. The portfolios are the Maximum Sharpe (MS) portfolio and the Minimum Variance (MV) portfolio.

Further, I assume that investments in EM stocks may generate a higher risk-adjusted portfolio return than investments in DM stocks by stating the following null hypothesis:

$$H0: IR = 0$$

In order to see the risk-return effects, I use the MSCI World Index as benchmark index. To estimate the risk-adjusted portfolio return, I use the CAPM and estimate the information rate (IR). The IR is a convenient measure of manager skill because it provides direct evidence of a successful portfolio strategy. In order to see what might cause my underlying hypothesis to fail, I estimate behavioural measures, along with different portfolio statistics.

In terms of this, I focus on active versus passive strategies. A passive investment philosophy is a philosophy where an investor believe that security analysis does not pay off. On the other hand, an active philosophy is where investors believe that it is possible to “beat the market” by actively search for a better outcome. Hence, the MS and MV portfolios are assumed active investment strategies. In order to get a comprehensive insight, I include a passive EM strategy that allocate stocks based on a “1/n” weighting scheme.

In order to test the validity of my underlying hypothesis, I will conduct asset-pricing estimation of my backtested portfolios and stock indices representing the BRICS. The asset-pricing models are based on the framework of Fama and French (1993). I use asset-pricing models to reveal anomalies. In academic research, the capital asset pricing model (CAPM) is known not only for its convenience, but also for its shortcomings. Therefore, I want to surpass the weaknesses of the CAPM and estimate the popular three-factor model. Further, I assume that world capital markets are integrated, and therefore extend the three-factor model to be a global five-factor model. I elaborate the variables in later chapters.

To achieve the objective of this thesis, I have chosen two different datasets. Both are of the same length, from 2001 through 2014 with monthly observations. The first dataset consists of large- and mid-capitalization EM stocks. I will use the first dataset to estimate and backtest portfolios. The second dataset consists of different size and style stocks representing the BRICS countries. I will not estimate and backtest portfolios of the second dataset, but will use it in asset-pricing models for a comprehensive insight and future research. To avoid noise in individual stocks, I have chosen to use country index portfolios. The data in this thesis were obtained from the website of Morgan Stanley Capital International.

I start the thesis by describing EMs. In chapter three, I discuss the ongoing debate about active versus passive investment strategies. In chapter four, I focus on literature related to this thesis and its implications. I focus on EM investments and the different investment vehicles that an investor can benefit from. In chapter five, I describe more in depth what data I use and the methods I use to answer my underlying hypothesis. In chapter six, I give an overview of own calculation on EM stocks. In chapter seven, I present the results of the out-of-sample performance of my backtested portfolios. In chapter eight, I estimate asset-pricing models to investigate my underlying hypothesis further. In the last chapter, I summaries my main findings.

2. What is an emerging market?

What really is an emerging market? Bodie, Kane and Marcus states; "a typical emerging economy is still undergoing industrialization, growing faster than developed economies, and has capital markets that usually entail greater risk". Godfrey (2013) stated that this equity class is unique by its growth potential and its eventual disappearance, that is, an EM reach its saturation point and, eventually, develops. One can distinguish three stages of economic development. First, we have frontier markets, the less developed economies. The second is emerging markets, which eventually, develops and belongs in the third category, namely developed markets.

Morgan Stanley Capital International (MSCI) uses a classification tool to classify a country to be represent one of the three categories. This classification tool place restrictions to the contribution of a country's economic development, size, liquidity and market access[1]. This framework is important to both buyers and sellers of a security in an international context. It gives a company the incentive to follow important guidelines, which attract new investor. Today, the MSCI emerging market index consist of 23 countries[2]. The MSCI offers a wide range of products and for benchmarking purposes, the indices are popular. For instance, SKAGEN Kon-Tiki A uses the MSCI Emerging Market total return index as its reference index. In table one, I present the constituents of the MSCI EM Index.

Table 1: Input list in MSCI EM index. Source: msci.com.

Latin America	***Europe***	***Africa***	***Middle-East***	***Asia***
BRAZIL	CZECH REPUBLIC	EGYPT	UNITED ARAB EMIRATES	CHINA
CHILE	GREECE	SOUTH AFRICA	QATAR	INDIA
COLOMBIA	HUNGARY			INDONESIA
MEXICO	POLAND			KOREA
PERU	RUSSIA			MALAYSIA
	TURKEY			TAIWAN
				THAILAND
				PHILIPPINES

Originally, the MSCI EM Index consisted of 10 countries back in 1988. Even earlier than this, EMs as an asset class have been important in allocation problems, especially because of their low correlation with developed markets. Today, in the standard capped

[1] For more descriptions see: http://www.msci.com/resources/products/indices/global_equity_indices/gimi/stdindex/MSCI_Market_Classification_Framework.pdf

[2] Source: http://www.msci.com/products/indices/country_and_regional/em/emerging_markets_index.html

index, over 800 securities represents the twenty-three countries. This represents approximately 13 % of world market capitalization. This shows the dynamics in economic development.

Historically, despite underperforming in some years, emerging markets as an asset class have exhibited stellar performance. As shown in the first figure, on an aggregated basis, EMs have yielded in excess compared with DMs on the long run. As usually characterized by EMs, we can see that the curve exhibits more spikes, indicating more volatility.

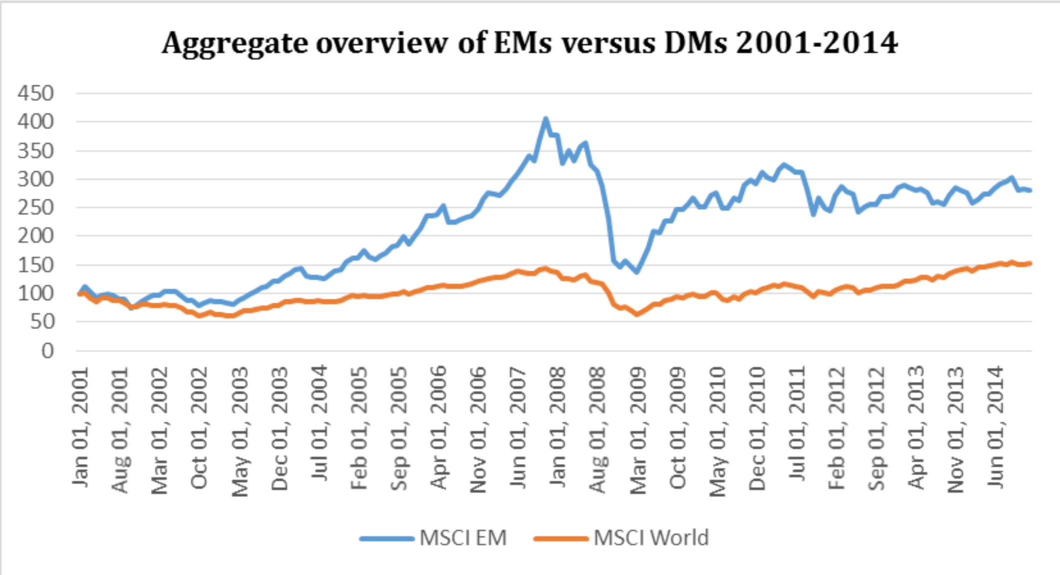

Figure 1: An aggregated overview of emerging- and developed markets in USD. Baseline at Jan. 01, 2001 = 100.

The BRICS countries are arguably the most important of the EM countries. BRICS is an acronym for Brazil, Russia, India, China and South Africa. One could believe that these countries, especially China, is to be part of the developed world. For example, by looking at the emerging economy of The United Arab Emirates, this economy is emerging by the lack of market structure despite that the economy is among the developed countries measured in GDP per capita. So, what really makes them different? In general, many believe that the distinction between emerging- and developed economies is not what it used to be. As globalization and trade liberalization have broken down tariffs and quotas, many market participants have experienced integration of markets. Two Harvard associates said in 2010 that «emerging markets misses important markets structures that differs from developed countries" (Khanna and Palepu, 2010). Khanna and Palepu (2010) also said that the link between buyers and sellers is inefficient and that this would imply higher transaction costs. To some extent, EMs are also characterized as lacking market openness. This criterion emphasises the gradual transition of an economy, in that a country moves towards being more integration with the world and connects with multilateral companies. Looking at China, the world's second largest economy, who became member of the world trade organization late 2001, had to relax over seven thousand trade barriers (economist, 2010). It is likely to believe that this includes relaxation of financial barriers as well. Nevertheless, China is one of twenty-three emerging markets.

When investing in EMs there are several important features to consider in the allocation process. When seeking diversification overseas it is important to look at the big picture. I will review some characteristics of EMs to get better insight in the nature of such economies.

As usually characterized by EMs, is the significant economic growth. For instance, China had a growth of 7.4 % in 2014, even though this was a downshift from previous years (Magnier et al., 2015). Compared with the US, its economic growth was "only" 2.4 % in 2014. Even though some EMs have experienced significant economic growth compared to DM's in recent years, it may not affect the stock returns. Recent authors have stated that GDP and equity returns do not have any relation in the short-term, but at best on the long-term (Godfrey, 2013). One of the reasons stated is because of the composition of GDP growth and composition of the stock market index differs significantly across markets. Similarly, in a discussion note by Norges Bank Investment Management (NBIM, 2012) they say that GDP growth is a bad determinant of a country's profit growth or EPS[3]. Rather, political and corporate risks are more suited to explain abnormal returns within EM stocks. EMs are associated with higher risk, and because of this, investors demand higher risk premiums. In an article by Amadeo (2014) she mentions three factors that increases risk in EM; natural disasters, external price shocks and political uncertainty. What regards external price shocks, it is highly relevant to consider oil price shocks to have an impact on EMs, such as India and Turkey, because they are net importers. Higher oil price slow down economic growth (Petroff, 2014). The oil price shocks can influence in different manners. As Basher et al. (2012) puts it, shocks affects future cash flows, interest rates and inflation. When interest rates rise in the US, foreign

[3] EPS: earnings per share ((net income – dividends) / total shares outstanding)

capital flows slow down because of the relatively less attractiveness of foreign direct investments (Thompson, 2014). Rising interest rates can have both positive and negative consequences, but works as a safe haven when there is instability world financial markets. Thompson (2014) said that the “The fragile five», an acronym for Indonesia, India, Brazil, South Africa and Turkey, suffered from this in the years of 2013-2014. In these years, the fragile five experienced slower growth, high inflation along with heavy dependence on foreign capital. In addition, if the dollar appreciates this makes it even worse for companies who borrow funds in USD. This is what the International Monetary Fund have feared recently. In a report by Crabtree (2015), the IMF was worried about balance sheets of banks, firms and household that borrow in USD because of strengthening of the USD this year. Further, IMF head, Christine Lagarde, encouraged EM governments to enact economic reforms and gradually liberalise financial markets.

Ahmed and Zlate (2014) examined the determinants of net private capital inflows into EMs. They examined pre-crisis determinates (2002-2008) and post-crisis determinants (2008-2013). The reason for examine this phenomenon was to get an understanding of underlying factors to economic distortion and policy changes. They found that growth differentials, interest rate differentials and global risk aversion were important determinants of net capital flows to EMs. The impact of the first two factors were positive, and negative for rising risk aversion.

3. Some basics on active versus passive strategies

An active strategy mean that you actively search for mispriced securities by yourself or hand the task over to a manager. Often, by passing over the task, will create economies of scale because the manager manages a much larger portfolio. Other the other hand, when you as an investor choose to not contribute in any form of security analysis, you will most certainly replicate a broad benchmark that will save you some time. Such an investor may choose to allocate funds in an exchange-traded fund (ETF). These types of investment vehicles have grown in popularity. This is because many believe that, on average, actively managed funds do not outperform passively managed funds. In 2003, there was 276 listed ETFs globally and by the end of 2013, this had grown to 3581[4]. These funds typically replicate a benchmark and a big advantage is that they are cheap. In comparison, mutual funds or hedge funds are investment vehicles that strives to beat the underlying benchmark. In these funds, the manager actively pursue securities that are mispriced.

The investors, whose strategy is passive, may suffer from the home-country bias[5] and do not get to exploit the opportunities within EM stocks. Put differently, we are saying that investors have pessimistic expectations about foreign equity or could be restricted by mandates. On the other hand, an active portfolio manager, tend to tilt the exposure toward EM stocks because of the opportunities of high rewards. The above comparison can be related to ETFs versus actively managed funds where the investor choose either one depending on risk aversion, costs, philosophy, time horizon, etc. Of course, both type of investors can invest abroad, but the distinction is how the funds are managed.

Where to put your money? That is the tough question. In the aftermath of the financial turmoil in 2008, the need to approach risk in new ways became clear. One of the world's largest banking and financial services organisations, HSBC, talks about passive strategies in an interesting way. While passive funds do not aim to outperform their respective indices, they have strong performance records compared with actively managed funds in efficient markets such as the US, UK and Japan[6]. The need and increased focus of transparency, transaction cost and liquidity has been major driving forces for this

[4] Deutsche Bank ETF annual review & outlook 2014.
[5] A tendency for investors/funds to underweight foreign equities.
[6] Source: hsbc.com; "why invest in passive funds with HSBC?"

approach. HSBC states that the active manager struggles to find mispriced securities in these efficient markets, due to all the available readily information.

Morningstar interviewed Joel Dickson of Vanguard about active versus passive strategies[7]. In the interview, Dickson said that the distinction is more about the cost than it is about intelligence or randomness of active management. He believes that minimizing cost will lead to success over time. As he puts it, the active approach is really about as you as an investor do have belief in a particular asset manager or active approach. Regardless of philosophy, one choose a manager that one believes give performance advantage and build around that manager with a passive strategy (Dickson, 2014).

Yet, the strategies considered is just two out of many. However, it is well known that, on average, active managers have not highlighted their superiority. Their cost inefficiency make them hard to believe and it is big difference in absolute and relative returns. The key is to stick with your plan and your value of investments. For example, Skagenfondene has an investment philosophy of value-investments. This means that they believe in so-called value stocks or unpopular stocks that have proven to outperform growth stocks on the long run. The subject is covered in later in the thesis.

A Morningstar article by Benz (2014) mentions some key attributes that investors often seek:

- *Low expenses*: Expenses on actively managed funds are generally higher than for passive funds.
- *Simplicity*: If you are looking for a low-maintenance portfolio, and do not manage or have time to monitor a well-diversified active fund, a tracker index fund or ETF is preferable.
- *Tax efficiency*: Index funds are usually constructed to be tax-friendly. Because active funds trade more, there is a greater likelihood that they pass taxable gains on to its shareholders.
- *Ability to beat the market*: You are not able to beat the market with a tracker fund. On the contrary, this is what the active approach strive to accomplish.

[7] Vanguard is one of the world's largest investment companies, offering a large selection of low-cost mutual funds, ETFs, advice and related services.

- *Flexibility*: This is undoubtedly on of the key advantage of active strategies. The active manager can adjust to changing market conditions. Thereby, withhold cash and ability to generate alpha.

With this in mind, we see the benefits of both sides. In terms of diversification benefits, a new approach has emerged. The traditional approach of diversification has been criticised because of the likelihood of "overdiversifying". This means at a certain point, you cannot achieve more benefits from diversification. On the other hand, some mutual funds specialize on specific industries such as consumer staples, telecom or technology, which implies that these funds could lack diversification. Rather, optimal diversification would be investing across industries and boarders. Therefore, the new approach to diversification is to diversify across funds. Arthur (2015), an Eaton Vance associate[8], said that they believe that the future diversification would be to allocate between investment styles rather than equity, i.e. active, passive and smart beta strategies[9]. However, the success of the implementation hinges on the ability of the investor to foresee cycles.

For many, it will be hard to find the preferred manager for its purposes, in addition to find the desired level of expenses. Pástor et al. (2014) did a study on scale and skill among 3126 actively managed domestic equity-only mutual funds form the US. They sort mutual funds by size and analyse their performance with time series and cross-section regressions. Overall, they found that larger funds experience lower transaction costs due to patience in trading. However, they found that there was strong evidence of decreasing returns to scale, indicating that the cost-return trade-off was not satisfactory. On average, large funds hold more liquid stocks, while small funds tend to reap premiums on stocks in firms with lower size, high book-to-market value and higher price momentum. This was an interesting finding, that a fund's preferences to hold a particular stock depends in part on the fund's size. On the other hand, Busse et al. (2014) argue that the underperformance of large mutual funds is not due to higher expenses, but the low average return their holdings offer.

[8] Eaton Vance, an investment management firm, provided this article on morningstar.com March 25, 2015.
[9] Smart beta strategies is a hybrid of passive and active strategies. The objective is to obtain alpha in a cost effective manner. The smart beta strategist may not use a standard index, but seek other areas of the market where it can exploit inefficiencies. Source: Investopedia.com

With that said, empirical research have contributed to the increasing popularity of passively managed funds due to their lower expenses and the average active funds' underperformance. Today, active managed funds face increasing competition that eventually will lead to lower expenses in the active industry as well. Especially, hybrids of funds are becoming increasingly popular.

In the indexing industry, there exist numerous vehicles. Morgan Stanley offers numerous of different indices that replicate strategies investors can follow. For instance, an investor that believe in behavioural finance can replicate a momentum index, which Morgan Stanley offer. Many have studied the momentum effect. For example, Li and Pritamani (2015) examine the momentum and size effect in emerging and frontier markets. They construct momentum portfolios based on past 6- and 12-month performance and find that the momentum effect decreases as the holding period increases. Specifically, momentum effects are stronger when based on the past 6-month returns. This suggests that in order to gain from the momentum effect the investor needs to rebalance a portfolio frequently.

As discussed in this chapter, there exist various investment vehicles to provide the desired level of exposure. I the next chapter, I will review literature on investments in EM stocks.

4. Literature review

4.1 Literature on emerging market investments

Investments in EMs have been characterized as risky, but with expectations of high rewards. In this literature review, I will focus on the rewards with investments in EM stocks. My review focus funds and indices rather than individual investors because of the benefits of larger managed funds and barriers to individual investors. The table below present the literature that I will review in this chapter.

Table 2: Literature overview of EM investments.

Author	***Year***	***Area of focus***	***Data***
Li, Sarkar & Wang	2003	Diversification	Stock indices
Driessen & Laeven	2007	Diversification	Stock indices
Bouslama & Ouda	2014	Diversification	Stock indices
Christoffersen, Errunza, Jacobs & Langlois	2012	Diversification	Stock indices
Bekaert & Harvey	2014	Market structures	Stock indices
Chang, Eun & Kolodny	1995	Diversification and alpha	Closed-end funds
Singh	2014	Alpha	Mutual funds
Dyck, Lins & Pomorski	2011, 2013	Alpha	Corporate & public pension plans
Huij & Post	2011	Alpha	Mutual funds
Eling & Faust	2010	Alpha	Mutual- and hedge funds
Guerico & Reuter	2014	Alpha	Mutual funds
Caglayan & Ulutas	2014	Alpha & predictability	Hedge funds

One of the motivating factors to invest in EMs are the possibilities of reducing risk. The five first papers focus on this aspect. In the context of international diversification, Li et al. (2003) find that increasing portfolio return is dependent on the degree of short sale availability of investors in the period of 1976-1999. When utilizing the Markowitz (1952) procedure, the estimation of the moments can lead to large leveraged positions. Li et al. (2003) used a dataset of stock indices in which eight were EMs and one representing the G7 countries. They used the mean – variance approach, where “δ” (delta) measured the increased expected return when going from the benchmark portfolio to the efficient portfolio. They also used the same technique to measure the decrease in variance. While they used Bayesian inference and Mote Carlo simulation to find the posterior distribution of weights, diversification benefits are obtained when one could leverage DMs to benefit from EMs. Moreover, their estimated global minimum variance portfolio illustrated that EMs provide sizeable diversification benefits to investors who are subject to short sale constraints. Driessen and Laeven (2007) find the same results for EMs. This study look at benefits of diversification from the perspective of local investors. Moreover, the benefits of investing abroad are largest for investors in DMs that seeks exposure particularly towards EMs, but also found that diversification benefits have decreased over the sample period of 1985-2002. While they believe that decreasing benefits are due to higher country risk over time, I believe that decreasing benefits are due to integration, in finance known as higher correlation between countries. This is consistent with the more recent findings of Bouslama and Ouda (2014), who also found that correlation between the country index portfolios representing EMs and DMs have increased in the sample period of 1988-2009. They also said that an investor should be cautious about investments in EM stocks, if not return is what is most important. In addition, they found that EMs should be included in an international portfolio if the presence of the asset class in a portfolio is not too substantial.

Christoffersen et al. (2012) find that diversification benefits have deceased for DMs but remain strong for EMs throughout the 1989-2009 period. This paper used weakly returns of sixteen DMs indices and two datasets consisting of weakly returns of thirteen and seventeen EM stock indices. In the paper, they said that while equity market crisis in EMs are frequent, the crisis tend to be country specific. Interestingly, they found that the diversification benefits from EMs are especially high in market downturns. Regarding country specific events, not all firm specific events can be dealt with. For instance, two of Skagen's stock funds (Kon-Tiki and Global) had in 2014 big unanticipated losses to a Russian company because of the arrest of the majority shareholder in the company and withdrawal of previously paid dividends (Skagenfondene, 2014).

Bekaert and Harvey (2014) studied the integration of EMs into world markets, in addition to whether one should view EMs as a separate asset class. They focused on various characteristics of EM indices to find an answer to their research question, such as correlation and beta against DMs, price-to-earnings ratios and a measure for market segmentation. In their paper, they found that EMs were segmented rather than integrated, measured by trade openness, investable equity and financial openness. They said, for example, that extreme political risk might effectively segment markets from global capital markets and keep out institutional investor because of restricted mandates. Thus, these factors can make investors demand higher expected returns. Bekaert and Harvey found that one should still view EMs as a separate asset class due to their segmented structures. Hence, diversification benefits still exists, though lower, because of increased correlation between equity markets and currencies.

All of the abovementioned papers illustrate that diversification benefits in EMs have changed over the years. Put in aggregate, EMs have become more integrated with the developed world, but their segmented structures still classifies them as candidates for diversification benefits. Nevertheless, in some instances, individual investors will find it difficult to achieve the same level of diversification benefits due to trading barriers overseas. A solution to this problem is funds in which invests worldwide. Various types of funds have opened the opportunity set for individual investor to get broader exposure other than their home country. Moreover, the following literature focus on such opportunity sets and to what extent the funds can add value to their investors.

Chang et al. (1995) investigated potential performance enhancement to investors in the US. In this paper, they focused on allocation of country closed-end funds that were located worldwide because the majority of investors do not have access to foreign markets. In addition to illustrate benefits of international diversification via closed-end funds[10], they analyse if the gains reflected any abnormal performance of the funds. They calculated Jensen's alpha for all country closed-end funds. Of the EM closed-end funds, only the Mexico portfolio obtained significant risk-adjusted return in the period of 1987-1990. Thus, for an investor in the 90s there was minor possibilities of achieving abnormal performance when allocating country closed-end funds.

A more recent paper by Singh (2014) investigate Canadian mutual fund performance from 1987 through 2011 which invest in fixed-income and equity securities in EMs. He used unconditional, partial- and full condition factor-models to estimate the alpha of the various funds in three different periods (1989-2000, 2001-2011 and 1989-2011) to assess the stability of the result. The main hypothesis was whether individual mutual funds or portfolios of funds obtained abnormal performances compared to the market. In addition, to measure the timing skill of funds, he used bootstrapped samples in which

[10] Closed-end funds are publicly traded investment companies in which issues a fixed number of shares through an initial public offering. Source: Investopedia.com.

illustrated whether performance was due to sample variation or timing. First, he considered portfolios of mutual funds. Using gross returns in the two-and five-factor model estimation, neither value- or equal-weighted portfolios of Canadian mutual funds had significant alphas. Using net returns in the same estimation, he found negative alphas in all periods for all funds, but only significant negative for the last sub-period. When he estimated alphas for individual mutual funds, the majority of funds exhibited zero alphas before and after fees. He conclude that most Canadian mutual funds are incapable of providing abnormal performances that cover their management expense ratios. In addition, he concludes that, on average, the mutual funds in the sample did not illustrate any market timing skills.

Inconsistent to the previous paper, Dyck et al. (2013) found that risk-adjusted returns generally are significant to active management in EM equity, but not in East Asia and Far East (EAFE) equity. A major contributor to this result, according to Dyck et al. (2013), is that institutional investors face lower cost relative to other active strategies. In this paper, they examined the use of active and passive management in non-US markets by institutional investors. Specifically, they use a panel data approach to analyse the performance of 492 US and 226 Canadian corporate and public pension plans, in the years of 1993-2008. They estimated various forms of factor models based on the Fama-French framework in a panel data approach and test whether the risk-adjusted returns of institutional investors were obtained thru skill or if risk had a price. The paper concludes that the advantage of investments in EMs stems from market inefficiencies and the sophistication of the investor.

As opposed to market efficiency, the paper of Huij and Post (2011) look at market momentum. They estimated performance persistence of 137 emerging market exposed mutual funds listed in the US in the years of 1993-2006. This paper is important to individual investors because it covers an investment strategy of behavioural finance. In this paper, they ranked EM funds every month by their return over the past quarter. Eventually, they had nine quantiles where the first quantile covered the best performers. Over the whole period, the results favoured the persistence of good performing EM funds, where the spread between the top and bottom quantile were 7.26% annually. They also report estimated alpha values for the whole period using the CAPM that were significant positive only for the top quantile. Furthermore, they investigated whether the persistence of the EM funds were attributed to exposure on the market factor, firm size, firm value and momentum. The estimation illustrated that none of the nine quantiles had significant alpha values due to attributes. The exposure to the momentum effect was significant for the top five momentum portfolios, indicating that performance was not attributed to skill of managers. However, the estimated alpha of the spread portfolio (winner minus loser) was significant, indicating that a momentum strategy in EMs is relatively more successful than in DMs. They concluded that this was due to less efficient markets in EMs.

In addition to mutual funds, the paper of Eling and Faust (2010) also focus on hedge funds performances. In this paper, they employed the same model to describe mutual fund's returns, but include extended models to capture the dynamics of such fund's returns. The variables were an equity market factor, the spread between the Russell 2000 Index minus the S&P 500, various MSCI EM region indices, two bond-oriented factors and three trend-following factors. They analyse the performance of 243 hedge funds and 629 mutual funds that focused on EMs in the years of 1995-2008. When using the EM factor-model to estimate alpha for an equal-weighted portfolio of all mutual funds, the estimated alpha was significant negative. This indicate that, on average, mutual funds underperform their benchmark. Looking at an equal-weighted portfolio of hedge funds, the estimated alpha was not distinguishable from zero. However, for individual hedge funds almost 12% outperformed their benchmark in EMs compared with only 0.95% of the mutual funds. To check the robustness of their results, they estimated alphas and factor premiums in the periods of Jan. 1996-Sept. 1998, Oct. 1998-March. 2000, Apr. 2000-Dec. 2006 and 2007-Aug. 2008. The estimation resulted in insignificant alpha values in all periods with a confidence of 95% for both mutual and hedge funds, with exposure to different emerging regions in every estimation. To investigate the different region exposure further, they calculated four different market scenarios (1 = worst months and 4 = best months) compared to the MSCI EM index. The result indicated that, on average, hedge funds provided downside protection in unfavourable market environments whereas mutual funds seemed to have relatively constant exposure to the same segments. Hence, this illustrated the flexibility of hedge funds in which they have the possibilities to allocate funds more active and use derivatives.

Another paper that also investigate the performance of hedge funds in EMs is the paper of Caglayan and Ulutas (2014). They examine how and why EM hedge funds can generate superior performance, if any, to their investors. This paper is an important contribution because it illustrates what exposure investor's faces when investing in global hedge funds. The dataset contains 1453 hedge funds in the years of 1999-2012. The EM exposure were estimated with these left-hand-side variables (LHS): MSCI EM Index, JPMorgan EM Bond Index Plus, JPMorgan EM Volatility Index, S&P Goldman Sachs Commodity Index, S&P Goldman Sachs Precious Metal Index and EM Currency basket index. The objective was to see the predicting power of betas of fund performance, and thus they estimated one-month-ahead fund returns on the factor betas. In the first stage, they estimated alphas and betas in a time series regression on a 36-month rolling window, and used these estimates with other fund characteristics in a cross-sectional regression. The cross-sectional regression illustrated significant positive betas of prior one-month returns, management fees, minimum initial investment requirement and liquidity risk. This indicated that higher betas of prior one-month returns, fees, initial investments and liquidity risk generated higher future returns. However, age of funds have significant negative effect on future returns. In the second section, they conducted test of beta-sorted portfolios with factor models to estimate alpha of a spread portfolio (high beta portfolio minus the low beta portfolio). They sorted hedge funds according to their betas of the EM equity index, EM Bond Index Plus and EM Currency basket index. Both the four-factor model and the nine-factor model revealed significant alphas for all three sorted beta portfolios. In the third section, they estimate alpha of the same spread portfolio, but control for the passive exposure to the MSCI EM Index. In this regression, they also found that the alpha estimates of the spread portfolios were statistically significant. The last section considers market timing of hedge funds and directional strategies[11]. The estimated market-timing coefficient was significant, which indicated market timing ability of the average directional strategist.

Typical for hedge funds are the large initial investment requirements. On the other hand, retail mutual funds, which are registered with the SEC[12], require lower initial investments. Guercio and Reuter (2014) examined such funds in the US and their

[11] Strategies in which the fund is willing to take direct market exposure and risk.
[12] Securities and Exchange Commission. Source: Investopedia.com

incentives to generate alpha. The paper do not specify where the funds invest, but can be generalized to EMs due to the different fund characteristics. The dataset cover 192 direct-sold and 153 broker-sold retail mutual funds in the years of 1992-2004. They pool all funds with data on various fund characteristics in a pooled OLS and panel data regression. In the first regression, they estimated the sensitivity of funds to generate risk-adjusted and raw returns. The dependent variable was the monthly net percentage flow to fund "i" in month "t". The independent variables were the lagged monthly net return and the lagged 4-factor alpha of Carhart (1997). They found that funds sold through intermediaries faced weaker incentives to generate alpha than retail mutual funds sold directly to retail investors, measured by the lagged alpha. However, on an unadjusted basis, future dollars flows to broker-sold funds were more sensitive, measured by lagged raw returns. They also illustrate that direct-sold funds are more sensitive by extreme movements, reinforcing the incentive of these funds to invest in skilled personnel. Due to the findings of sensitivities in dollar flows, direct-sold funds had stronger incentives generate alpha, while broker-sold funds were more likely to bear systematic risk. The direct-sold funds were significantly more active measured by a dummy, suggesting that they are more likely to be stock pickers. In the last regression, they pool all funds and estimate the risk-adjusted return against index funds with a dummy variable. They conclude that the persistent underperformance of actively managed funds compared to index funds was driven by broker-sold funds. Based on these findings, it is important for investors knowing what strategies different funds follow. If the findings of Guercio and Reuter (2014) can be generalized to the whole mutual fund industry, investors are better off choosing direct-sold funds or ETF's reaping risk premiums of risky stocks.

There are mixed results in the literature review. Some indicate evidence of significant risk-adjusted performance in EMs due to attributes such as market inefficiencies and investor sophistication. Moreover, institutional versus retail investors face different exposure and expense ratios. Due to restricted mandates, institutional investors will not necessarily benefit from EM exposure. Sophisticated investors does provide exposure to EMs, in addition to hedge unfavourable market movements. In addition, allocation of funds to EMs is likely to generate diversification benefits due to their country specific market movements.

4.2 Literature on asset-pricing models

In this sub-section, I will discuss factor models and its inference related to EMs. Primarily, I focus on the Fama-French three-factor model. In order to estimate reliable estimates of the premiums in a multifactor model, Van Dijk (2011) mentions that the number of time series observations, securities and sorted portfolios are crucial.

The Fama-French framework have been criticized by for example MacKinlay (1995), Black (1993), Berk (2000) and Lambert and Hubner (2014). The critique focuses on the validity of the Fama and French (1993) procedure. MacKinlay (1995) argue that their findings of were only by chance and biased due to data mining[13]. The idea is that the SMB and HML factors are empirically motivated variables that correlate with stock returns just by chance, and thus have higher probability of type one and type two errors. Berk (2000) analyse the theoretical implication of sorting data into groups and then running asset-pricing tests within each group. He shows that by sorting stocks in groups based on a variable that is only known to correlate with returns, the explanatory power of the model will always be smaller within a group than in the whole sample. Thus, rejecting models that may be correct pricing models. Another paper discusses the issue of data mining. Black (1993) said that the anomalies in research studies are likely to be a result from data mining. He said that because there are so many researchers that scan roughly the same datasets for investment opportunities, a chance that one of them might find a successful one is not unrealistic. Even worse is when only the successful examinations are published. Then, when somebody use it, they will follow the same blind alley. One surely will not know what will happen in the future and an anomaly will vanish as soon as it is discovered. Black (1993) also claims that the results of Fama and French are attributable to data mining. Especially, his critique is about that Fama and French do not explain what the SMB and HML might be. He argue that the risk premiums of small firm stocks and value stocks could be due to irrational pricing and inefficient markets.

On the other hand, the data mining problem was challenged by Van Dijk (2011). He examined the international evidence of the size premium and said that if the effect exists in different markets in different time periods it is evidence against data mining.

[13] Data mining is referred to as finding statistical significant results only by chance. When you "snoop" around in a sample, some correlation between data will eventually exist.

Moreover, he also examined the effect for the purpose of investment decisions because the size premium could be dependent on characteristics such as trading mechanisms, investor behaviour, liquidity and market efficiency. For the size effect, out-of-sample tests are needed to counter the data mining argument. Further, he said that the inference of the validity of small stock premiums is not straightforward because stocks are very noisy and standard errors around the size premiums are large. Van Dijk (2011) argue that further investigation is needed to establish the validity of the size effect because there are many factors that can explain the anomaly. His examination is also relevant regarding the value premium in the HML factor. As a result, he argues it is premature to draw conclusion on anomalies without thorough analyses.

Furthermore, in the spirit of Van Dijk (2011), I present literature that has investigated the size and value anomalies in different periods with different datasets. I should specify that size and value effects indicated by "yes" means a premium on small firm stocks and value stocks in the SMB and HML factors, respectively. I review papers that have use both time series and cross section regressions. Time series regressions are used to estimate factor loadings to be applied in cross section regressions to explain the cross section of average stock returns. Hence, I should also specify that I only use time series regressions in my analysis.

Table 3: Literature overview of asset pricing estimation.

Author	***Sample***	***# stocks***	***# portfolios***	***# EMs***	***Size effect?***	***Value effect?***
Barry, Goldreyer, Lockwood & Rodriguez	1985-2000	2000	25	35	No	Yes
Cakici, Fabozzi & Tan	1990-2011	5200	25	18	No	Yes
Xu & Zhang	1992-2013	-	25	China	Yes	Yes
Sehgal, Subramaniam & Deisting	1994-2011	2475	30	6	Yes	Yes
Drew, Naughton & Veeraraghavan	1990-2001	387	6	China	Yes	No

Barry et al. (2002) used a cross-sectional regression to describe return patterns in 25 size- and value-sorted portfolios. They observed significant positive value premiums for 72% of the individual EMs in the period (higher returns for value stocks). However, they find it difficult to estimate reliable significant size premiums in EMs. They illustrated the problem by deleting the January returns because small stocks exhibited extreme returns in this month. They provide a comprehensive set of results to find robustness in their conclusions. Hence, the size effect may be biased due to the January-effect, also explained by Van Dijk (2011).

Although Cakici et al. (2013) focused mainly on the value and momentum effect, they estimated that the return of the SMB portfolio was not statistically different than zero, indicating that small and large stocks have similar return patterns. The rational explanation is that market participants have arbitraged away this premium. However, the value premium was present in all regions studied: Asia, Latin America and Eastern Europe, including a portfolio of all EMs. They used the GRS statistics to test the joint significance of alphas in cross-sectional regressions of their four region-sorted portfolios. To explain returns, they experimented with SMB and HML factors based on US, global and local EM stock data. When LHS variables were sorted on size and book-to-market value, they reject that the intercepts are jointly equal to zero for all models. However, the local model did a better job capturing return patterns indicated by higher R-squares, lower intercepts and lower intercept standard errors compared to the other asset-pricing models.

Sehgal et al. (2014) used size and book-to-market value sorted portfolio to examine the size and value anomalies. They illustrated largest size premiums in the SMB factor for Brazil and smallest for South Africa, while the value premium in the HML was largest in Indonesia and smallest in China. In the time series regression, they used the inverse of the HML factor. The three-factor model explain the size anomaly in the size-sorted portfolios in Brazil, China and Indonesia, but not in India and Korea indicated by significant alpha values. Regarding the value-sorted portfolios, the three-factor model failed to explain the value anomaly in South Africa and Korea due to significant alpha values of these country portfolios.

Drew et al. (2003) found divergent results for value stocks in the Chinese market. Empirical findings have suggested that value stocks are more prone to distress than growth stocks and therefore should have a premium. In their sample, they found that growth stocks had a premium. They gave an interesting interpretation in that Chinese investors have overexploited the value premium in a sense that the detected pattern of mispricing has been arbitraged away. In this sample, the Chinese stock market is a rational market. However, the Chinese market participants had not arbitrage away the size premium in the SMB factor. Therefore, they suggest another interpretation that

Chinese investors act irrationally by their inability to process information. In the time series regression, they illustrated that the intercepts were indistinguishable from zero on the six size and book-to-market sorted portfolios. The size factor was significant positive for all three small stock portfolios and insignificant negative for two of the large stock portfolios. The HML factor was significant negative for all six stock portfolios, indicating a positive premium. Thus, they argue that the premium was in line with the literature, but not the means of finding it.

The more recent study of Xu and Zhang (2014) experimented with sub-periods as well as the whole sample period. This paper examined the Chinese stock market in the years of 1993-2013, and the factor model showed persistent premiums on both SMB and HML factor, though on tradable assets. They obtained an average R-square value of 93% on the 25-sorted portfolio by using local sorted size and value portfolios to explain variation in stock returns. However, when they included US stocks representing the size and value factors to explain Chinese stock returns, they do not find any explanatory power.

This literature review rises important questions about the inference of factor models. I have to be aware of the several pitfalls along the estimation such as data mining, outliers, estimation bias and sample selection bias. The existence of the size and value premiums of the SMB and HML factor are highly debated. There are also different findings of how they are related to size and value sorted portfolios. As far as I know, there are more research on the size and value effect and their role to explain return variation in the developed world especially in the US.

Next, I present the data and the methods I use to answer my underlying hypothesis.

5. Data and methodology

I will use two different datasets to answer my research question. Both dataset spans over a fourteen-year period in January 2001 through December 2014, on a monthly basis. In the first dataset, the stock indices of Qatar and the United Arab Emirates have missing values, and therefore I have excluded them. I am aware of the sample selection, and it could possibly be a drawback because it limits the representation from the Middle East region.

The datasets used in this thesis are from Morgan Stanley Capital International. The data is total return indices with net dividends measured in US dollar. All calculations or illustrations are in USD unless stated. The first dataset contains 23 emerging market indices that are large- and mid-capitalization stocks, along with one index representing developed markets. In order to see the risk-return effects, I have chosen to use MSCI World Index as the benchmark index. The developed market index (MSCI World) represents 23 developed countries as shown in table thirteen in the appendix. All indices are assumed investable. For the riskless alternative, I have used 5-year US treasury obtained at quandl.com. The data of the treasury yield is also monthly. For instance, to estimate excess returns, the riskless alternative is used.

With my first dataset, I have chosen to estimate three types of portfolios to display the possibilities with investments in EM stocks. The first two portfolios are assumed active strategies, where I actively search for the best outcome. The third is for the means of a passive investor that will not contribute in any form of security analysis. Hence, the three portfolios are the Maximum Sharpe (MS), Minimum Variance (MV) and the naive "1/n". The naïve portfolio is beneficial because it is easy to implement and does not rely on estimation of the moments of asset returns. In addition, the naïve portfolio is included to illustrate the outcome of a different weighting scheme than the benchmark.

By applying the backtest, I can estimate the risk-adjusted portfolio returns. The purpose of the backtest is to test fictitious strategies based on in-sample data. Of the out-of-sample performance, I can estimate the risk-adjusted portfolio returns relative to the benchmark index. The backtest is convenient because there is no look-ahead bias. If the predictions in the backtest were reliable, the investor could gain momentum of this procedure.

The first in-sample period, and thus my expectation about the future, starts with the first five years of the sample: January 2001 through December 2005. This first in-sample estimates of the 21 EM indices, produces weights to hold one month: January 2006. Then, I use a rolling window of five years to re-estimate optimal combinations to hold in the subsequent months in a time horizon of nine years ending in December of 2014. This provides 108 re-estimated samples with 108 re-estimates of expected return, variance and covariance. The procedure leads to rebalancing of the portfolios if the optimal weights change. When I estimate the portfolios, the weights are highly sensitive to the input data. By using an in-sample period of five years, a trial and error technique is the best way to find out what input data is correct. I will stick to my technique and not contribute in any form of data snooping. Since the series begins in a post-crisis period of the dot-com bubble, I believe that the data is representative in a way that it captures a "new start". The data also captures a more recent drawback in the economic and financial markets, and it is therefore interesting to see how the portfolios react to this event. In addition, because the portfolio optimization is highly selective, only a few stocks may be preferred to hold. It is likely that an investor would disagree on that matter because the representativeness within some of the country indices are inadequate. Because the Markowitz (1952) procedure can favour large leveraged positions, I forbid short selling.

In order to see if my portfolios have generated a higher risk-adjusted portfolio return than the benchmark index, I use the information rate (IR). The IR is based on the CAPM:

$$R_{i.t} - R_{f,t} = \alpha + \beta\left(R_{m,t} - R_{f,t}\right) + \varepsilon_t$$

Where "$R_{i.t}$" is the excess return of portfolio "i", "$R_{m,t}$" is the excess return on the market portfolio, "α" is Jensen's alpha, "β" is the market premium and "ε_t" is the error term. In order to estimate the IR, I divide Jensen's alpha on the residual variance. In order to test my null hypothesis, $H0$: $IR = 0$, I estimate the t-value of the IR as IR * sqr (N), where "N" is number of observations.

As far as portfolio success concerns, Hagin and Kahn (1990) said that outperformance may solely be due to luck. They said that the backtest must demonstrate that the active return of a portfolio relative to a benchmark, with reasonable certainty, is due to skill and not luck. To overcome this issue, an appropriate measure to use is the IR. It measures the return from active management over the benchmark index. For an active portfolio manager to increase the IR, he has to either increase alpha or reduce the unsystematic risk. However, if the IR shows ratios above 2.0, I have to examine the results carefully. An information rate above 2.0 implies possession of inside information. Moreover, I divide the 108 out-of sample months into bull and bear months to test monthly behaviour. Success in bear months means less drawdown than the benchmark index. Likewise, success in bull months means higher gain than the benchmark index. In addition, because of the relevance of cost, I have estimated turnover. I estimated turnover for each month, by dividing today's new constituents on today's total holding. For example, if a portfolio holds 10 stocks the previous period and hold 10 today, but 5 stocks is new, the portfolio turnover will be 50%.

In order to investigate potential diversification benefits, I have estimated Sharpe ratios and tested for equality in variances and means. The portfolios are not investment proposals, but by the means of illustration. I have to be aware of different biases such as survivorship bias and the look-ahead bias. In fact, using MSCI constituent history datasets help me avoid such problems. They construct indices such that the samples are reliable when backtesting[14]. The MSCI indices are continuously updated and restructured[15]. Quarterly reviewing of the indices takes place in Feb, May, Aug and Nov, while limiting undue index turnover. Rebalancing and recalculation takes place on a semi-annual basis of the large- and mid-cap cut off points.

I dedicated my second analysis to cover asset-pricing models. This applies to time series analysis with estimation of factors premiums that could possibly explain anomalies. In fact, a significant risk-adjusted portfolio return could be a premium on risky assets. If the portfolios signifies exposure to risky asset, a passive replication strategy is likely to perform better due to lower cost.

In this sense, I will use the framework of Fama and French (1993) to estimate factor premiums. In the first asset pricing section, motivated by Dyck et al. (2013), I will estimate factor premiums of the backtested portfolios. Asset pricing estimation is

[14] Source: MSCI constituent history (msci.com).
[15] Source: factsheets available at msci.com

convenient as performance evaluator of mutual funds, especially the extended version of Carhart (1997) with a momentum factor.

In the second asset pricing section, I use my second dataset, which is style portfolios representing the BRICS. The reason why I have chosen a different data set is that my first dataset does not represent the whole aspect within EM stocks. There are two reason why I have chosen the BRICS. First, they are arguably the most important of the EM countries. Second, the BRICS country indices are among the most diversified because of the number of constituents in these indices. In order to be similar to the original procedure, I have chosen the BRICS to be combinations of value-, growth-, small- and large stock indices. Thus, I estimate factor premiums of 20 portfolios. By expanding the data set, I can estimate and find evidence against the view that the market beta of the CAPM is the sole measure of risk (Drew et al. (2003)).

I use index portfolios rather than individual stocks, because they are more diversified and are less likely to bias the estimation. Jensen et al. (1972) said that individual stocks exhibit unsystematic risk that are more likely to make factor models biased. They said that since the cross-section of error variance is not independent, a more accurate way is to diversify away the noise and use grouped data. EM stocks are also known to exhibit more risk and, as we will see in the descriptive chapter, have high residual risk. However, individual stocks in EMs are probably noisier. Because I use portfolios, my estimation is advantageous.

The right-hand-side (RHS) variables in the factor models will be approximately the same as the Fama-French variables. They used a ranking system to cover all combinations of stock size and book-to-market value, i.e. small/low, small/medium, small/high, large/low, large/medium and large/high. Because of data limitations, I got a 2*2 ranking system, i.e. small/low, small/high, large/low and large/high.

The estimation will be with the CAPM of Sharpe (1964), Lintner (1965), and Black (1972), a local version of Fama and French (1993) three-factor model and a global five-factor model. The local size and value portfolios will be representation of small- and big-capitalization and value and growth stocks of the MSCI EM Index. The global versions of the size and value portfolios will be the same styles and size, but I use the MSCI World Index that represents developed markets. The models are:

1) $R_{i,t} - R_{f,t} = \alpha + \beta\,(R_{m,t} - R_{f,t}) + \varepsilon_t$
2) $R_{i,t} - R_{f,t} = \alpha + \beta\,(R_{m,t} - R_{f,t}) + \beta\,SMB^{local}{}_t + \beta\,HML^{local}{}_t + \varepsilon_t$
3) $R_{i,t} - R_{f,t} = \alpha + \beta\,(R_{m,t} - R_{f,t}) + \beta\,SMB^{local}{}_t + \beta\,HML^{local}{}_t + \beta\,SMB^{global}{}_t + \beta\,HML^{global}{}_t + \varepsilon_t$

Where "$R_{i,t}$" is the excess return of portfolio "i", α is the intercept, "$R_{m,t}$" is the excess return of the market portfolio, the SMB's and HML's are the mimicking portfolios of size and book-to-market value (B/M), and the error term, "ε_t", assumed independently and identically distributed (i.i.d). The SMB variable is essentially a portfolio of small capitalization stocks minus a portfolio of big capitalization stocks, thus SMB (small minus big). Likewise, the HML variable is a portfolio of high B/M stocks minus a portfolio of low B/M stocks, thus HML (high minus low). These are zero-net portfolios that measures the sensitivity of a security to movements in small stocks and value stocks. Low B/M stocks are called growth stocks. The SMB and HML variables are not themselves obvious candidates for relevant risk factors, but they represent a proxy for other relevant sources of systematic risk (Bodie et al., 2014). According to Fama and French (1993), a factor model is correctly specified when the estimated intercepts are indistinguishable from zero. The t-values of the alphas provide evidence of its existence. In addition, the estimated betas and R-squares gives direct evidence of the relation between the variables.

If markets are integrated, there should only exist one set of risk factors. Therefore, I assume that the best model to describe variation in stock returns is the global model. The market factor will be the same throughout the thesis. However, I am aware of the potential bias in selecting the wrong market portfolio.

Due to potential biases in time series regressions. I check for all problems regarding the Gauss-Markov assumptions according to Wooldridge (2014). I test for stationarity, perfect collinearity and assume exogenous explanatory variables. I also check for heteroskedasticity and serial correlation in the residuals. I adjust the standard errors with HAC[16] standard errors if the models display such problems.

[16] HAC = "heteroskedasticity and autocorrelation consistent" standard errors.

6. A descriptive overview of emerging markets 2001 – 2014

What are the characteristics that an investor will face when seeking exposure to EMs? In this section, there will be comparison of return and volatility characteristics in emerging markets and the developed world. I will first consider return characteristics. Further, I will illustrate how volatility has evolved. In the end of section six, there is a summary table of descriptive statistics of all emerging market indices, the world market index and the emerging market index. I use geometric return calculation in my sample.

6.1 Emerging market equity return

As we see in figure 2, measured in annualized total returns, emerging markets have performed better than the developed world in 10 out of 14 years when hedged in USD. In the early 2000's until the financial crisis, emerging markets have consistently outpaced the developed world. Over the period as a whole, if an investor would have hold a long position in the MSCI EM index, the return would have exceeded that of MSCI World index by 79 percentage points (given that the position is hedged in USD). The gain compared to the world index is even more significant when considering local currency, which is 96 percentage points, given a long position. Looking at a position when hedged USD, the emerging market index gained positive returns in 8 out of 14 years, while developed markets had positive returns in 10 years. The situation reverses when looking at an unhedged position, where emerging- and developed markets have 11 and 10 years of positive returns, respectively. This illustrates the importance of currency risk when investing in stocks abroad.

Figure 2: Annual cumulative returns of emerging- vs. developed markets in USD.

The emerging market index achieved an annual average return of 10 % over the sample period. This is in excess compared to the MSCI World index by 600 bps. However, the MSCI World Index is not as affected by large fluctuations compared to emerging markets. Emerging market performance in recent years might have been a disappointment for investors. With a reputation of being big risk compensators, and looking from an aggregated view, emerging markets did not live up to this reputation the last four years. Depending on investment horizon, certain years favors developed countries. In an annual report by Deutsche Bank January 2014, they found that within the ETF industry in 2013, equity based ETFs lost traction in emerging markets and one could see an increased focus on developed markets. According to Deutsche Bank annual overview, EMs had outflows of $19.3bn in 2013, in contrast to inflows of $53.3bn in 2012.

What really influences the index to perform as it does[17]? From an aggregated view, it is hard to judge. A better way of finding out is to look at each country in the MSCI EM Index. In table 4 at the end of chapter four, we can see how each country, represented by an index, performed on average during the period 2001-2014. Colombia and Peru had the highest average annual returns of all the countries, closely followed Indonesia, Egypt

[17] Visit the appendix and see table 15 to get an overview of the MSCI EM Index and its constituents.

and Thailand. They also gained the highest average Sharpe ratios. Colombia, with its relatively small weight in the MSCI EM index, performed best on average among all emerging markets. Peru also performed among the top countries. Despite Peru's small number of constituents, its representation is attractive. Because of Peru's small number of constituents, the big question is; does these three constituents compensate for the risk taken, and is Peru performing at its expected best? Assuming that the Peru index is a portfolio itself, one could argue that this is not a well-diversified portfolio. Small number of constituents is the case for some of the EMs. This includes Egypt, Czech Republic and Hungary. Since I use the "standard indices" of MSCI to estimate portfolios, the country indices represents less of total country capitalization. However, by using these indices I exclude noise form the series.

For the rest of the Latin American countries, their performance were not unlike their mother index, MSCI EM Index. Due to riskiness of these countries, their mother index had a better risk-return trade-off. Compared to the MSCI World Index, they have a better risk-return trade-off. As a group, Latin American stocks had the highest average return of all regions.

With its relative small weight in the MSCI EM Index, the Middle East region performed poorer than the MSCI EM index (not reported in the table). However, only Qatar gained annual average returns in excess to the benchmark, MSCI World.

For Asian countries, Indonesia performed best on average, during the sample period. It also had the best risk-return trade-off, closely followed by Thailand. However, Thailand is victorious regarding compensation of risk in the left tail. It gained the highest Sortino statistic. As for the rest of Asian countries, they are close to the sample average return, with exception of Taiwan. The Asian countries also constitute the highest weight in the MSCI EM index.

Of the two African markets, Egypt had the best risk-return trade-off. South Africa has much bigger weight in the MSCI EM index with its 51 constituents. As an asset, South Africa is more stable on average and contain less uncertainty.

The main finding in the emerging European markets is that this region had the poorest risk-return trade-off of all emerging regions. The clear winner in this region is Czech Republic, while Greece illustrates poor statistics. Czech Republic, according to the OECD economic outlook, has since the recession had steady economic growth and decreasing unemployment rate. These indicators may explain some of the ongoing good trends in the country. With its few constituents in the index, I may by sceptic about its contribution.

I can see that out of 21 EMs, only seven have significant mean difference to the benchmark index. However, in economic terms, without considering the downside, every country, except Greece, have higher gains on average. What can we make out of this? The MSCI EM Index illustrates that, some years do not favor emerging markets, but a buy-and-hold strategy over the whole period, has favored EM stocks.

6.2 Emerging market equity risk

Emerging market equity exhibit more risk than their developed counterparts do. As shown in the figure 3, I have ranked the respective country indices from less risky to the riskiest, along with the benchmark index. On average, the most risky country is Turkey at 48% annually. Interestingly, Turkey exhibits the highest beta among the countries with a beta of 1.9. This indicates that the return series of the Turkey index is almost twice as sensitive to price fluctuations in the benchmark index. I wanted to estimate the betas of the EM stocks discussed in this chapter. Along with the beta of each market, I calculated the average return of each market when the World Index exhibited positive and negative returns. As we can see from table 16 in the appendix, the beta almost consistently overestimates the downside and underestimates the upside for every country. This indicates that the return series are somewhat skewed.

While considering Turkey as European in this thesis, the European region is the riskiest region with an average standard deviation of 36%. This is equivalent to the betas to the respective European countries, which averages at 1.6. Thus, according to the CAPM, European markets are more sensitive than an average market. Therefore, because of relatively high betas along with high variance, we would expect a higher correlation from this region to the developed world.

As figure 4 illustrates, there are big differences in risk profile among the countries. The least risky country is Malaysia, which is the only country that does not reject the equality in variances test. Malaysia also has the lowest beta, although we do reject it to be zero. The Asian region has been the least risky, on average, with an annualized standard deviation of 27%.

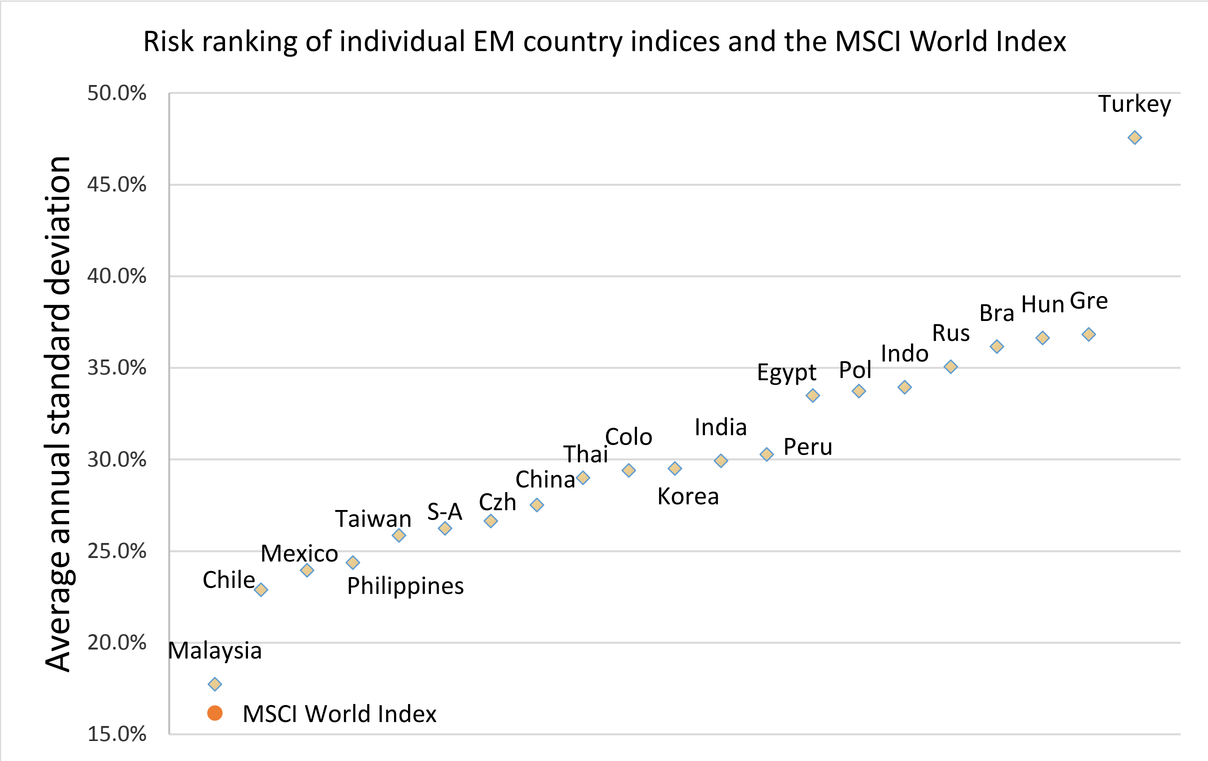

Figure 3: Risk rank system of EMs over the sample period 2001-2014.

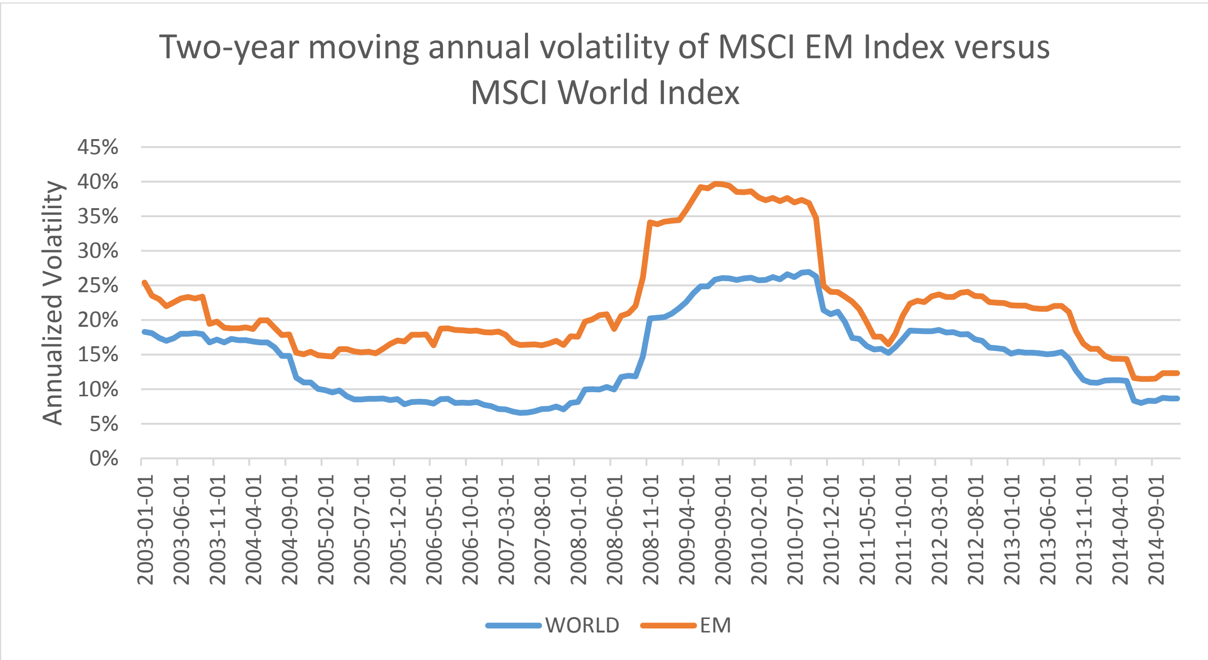

Figure 4: Aggregated overview of risk comparing the benchmark index and EMs.

If I aggregate each EM into one index, I can compute a rolling window of two years of volatility. In figure 4, the lines illustrate the development in risk. I see that EMs have been consistently more volatile during the whole period, although closer in 2003-2004 and 2011-2014. We can see a sharp rise in standard deviation in 2008 in both emerging- and developed regions that continuous for two years and falls back to their respective average values of 23% and 16%.

The standard deviation may be a bad measure of risk in this context because all the countries reject the normality assumption. In fact, all countries exhibit negative skewness and positive kurtosis. This is problematic for investors because the standard deviation of the return series will underestimate risk. Likewise, the positive kurtosis will make the standard deviation biased because of fat tails, implying higher probability-mass in outliers. With this in mind, it is more appropriate to use measures that captures vulnerability to extreme events.

As illustrated in table 4, the statistical properties of the EMs are in fact the same. I have included the 1% Value at Risk (VaR) and 1% Expected shortfall (ES) measure. At the first percentile, European EMs have the worst outcome. When finding ourselves in the worst-case scenarios, ten countries have had greater probability of loss under 30%. These are Brazil, Peru, Greece, Hungary, Poland, Russia, Turkey, Indonesia, Thailand and Egypt.

Until now, I have illustrated stock market characteristics. Are there possibilities of achieving diversification benefits within EM stocks? I know that each market entails greater risk than the DMs, but nothing about residual risk and how EMs correlate with the industrialized world. For a portfolio manager low correlation between securities is preferable.

Because I chose the MSCI World Index to be the benchmark index, it has no residual variance. The MSCI EM index has much lower residual variance than the individual EMs, because it is more diversified. Therefore, it should be possible to eliminate some of this risk when allocation the country indices.

In figure 5, I illustrate correlation on a monthly basis by rolling 24 consecutive months between emerging regions and the benchmark index. The region view is interesting because it is easier to see how the each region interacts with the world.

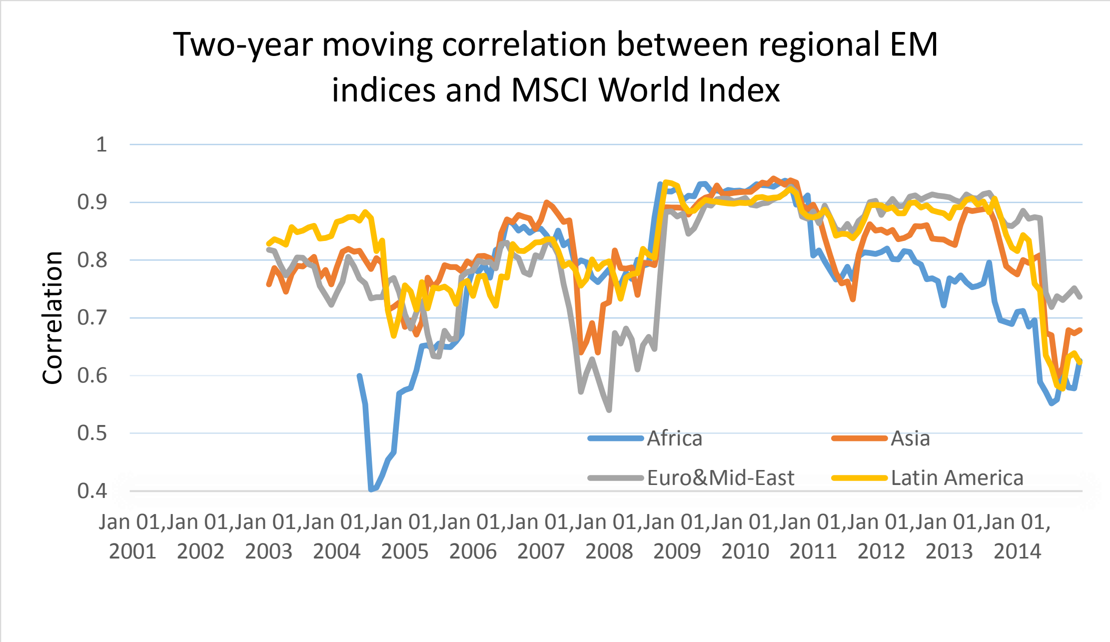

Figure 5: Overview of correlation between emerging regions and the World Index. (index names: EFM Africa, EM Asia, EM Europe & Middle East and EM Latin America).

Rejection of the null hypothesis of zero correlation is the case for every market and the MSCI EM Index. The correlation between the MSCI EM index and the World index has increased. Correlation in the period 2001-2007, was at 0.83, while increasing in the period of 2008-2014 to 0.91. The graph illustrates that this is not consistent with the emerging regions. The last two years have highlighted diversification benefits to a higher extent in these regions. In figure five, the African region has been the least integrated region. However, the fact that the Africa index represents both frontier and emerging markets, the graph does not illustrate the real picture of EMs separately. Second, for further analysis the drop in correlation at the beginning of 2008 should be kept in mind. When I illustrated risk profiles for the same period, I observed a sharp upward trend. The interesting thing of this comparison is that while correlation drops, for all regions, risk tends to rise. This phenomenon may be due to shocks in a region or markets that are dependent on events within each individual market. Because of this, one could believe that EMs possesses diversification benefits in bull markets.

Table 4: Descriptive statistics of EMs, MSCI EM index and the benchmark. Test statistics in bold indicates statistically significant at least at 5% level. P-values for normality are significant when p<5%. Null for mean and variance is equality. Null for beta and correlation is equal to zero.

	Latin America					Europe					
	BRA	*CHILE*	*COL*	*PERU*	*MEX*	*CZE*	*GRE*	*HUN*	*POL*	*RUS*	*TUR*
Annual performance											
Average return	10%	9%	24%	20%	12%	14%	-11%	5%	6%	9%	8%
Sharpe	0.20	0.26	0.74	0.55	0.40	0.44	-0.37	0.05	0.08	0.17	0.10
Sortino	0.31	0.42	1.28	0.89	0.62	0.72	-0.52	0.07	0.13	0.27	0.15
Information rate	0.03	0.08	0.24	0.17	0.15	0.14	-0.20	-0.03	-0.02	0.03	-0.01
Standard deviation	36%	23%	29%	30%	24%	27%	37%	37%	34%	35%	48%
Residual risk	24%	17%	25%	26%	14%	19%	26%	24%	21%	26%	36%
Best month	25%	18%	22%	24%	16%	18%	27%	24%	25%	28%	37%
Worst month	-39%	-30%	-33%	-45%	-37%	-35%	-46%	-57%	-41%	-44%	-53%
Beta w/World	1.7	0.9	1.0	1.0	1.2	1.1	1.6	1.7	1.6	1.5	1.9
Correlation w/World	0.76	0.67	0.54	0.53	0.82	0.69	0.72	0.75	0.79	0.68	0.65
Normality Check											
Skewness	-0.78	-0.83	-0.54	-0.98	-1.18	-0.70	-0.83	-1.31	-0.57	-0.74	-0.64
Kurtosis	1.86	2.82	1.33	3.98	4.55	2.35	2.27	4.94	1.68	1.83	1.51
VaR 1%	-37%	-23%	-25%	-28%	-23%	-25%	-39%	-40%	-33%	-32%	-46%
ES 1%	-38%	-26%	-28%	-35%	-29%	-29%	-42%	-47%	-36%	-37%	-49%
Tests											
Normality test (p-value)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%
t-test for mean	0.8	1	**3**	**2.2**	**2.1**	**1.9**	**-2**	0	0.2	0.6	0.3
F-test for variance	**5**	**2**	**3.3**	**3.5**	**2.2**	**2.7**	**5.2**	**5.1**	**4.4**	**4.7**	**8.7**
s.e (beta)	0.11	0.08	0.12	0.12	0.07	0.09	0.12	0.12	0.10	0.12	0.17
t-stat (beta)	**14.9**	**11.5**	**8.3**	**8.1**	**18.5**	**12.3**	**13.3**	**14.8**	**16.4**	**11.9**	**11**
t-stat (correlation)	**14.9**	**11.5**	**8.3**	**8.1**	**18.5**	**12.3**	**13.3**	**14.8**	**16.4**	**11.9**	**11**

	Asia								Africa			
	CHI	*IND*	*INDO*	*KOR*	*MAL*	*TAI*	*PHI*	*THAI*	*S-A*	*EGY*	*EM*	*WORLD*
Annual performance												
Average return	10%	12%	19%	13%	10%	6%	12%	17%	12%	17%	10%	4%
Sharpe	0.27	0.31	0.49	0.33	0.42	0.12	0.36	0.48	0.35	0.41	0.30	0.09
Sortino	0.42	0.51	0.78	0.58	0.71	0.20	0.62	0.81	0.56	0.72	0.47	0.14
Information rate	0.08	0.09	0.15	0.10	0.15	0.02	0.12	0.15	0.11	0.12	0.11	
Standard deviation	28%	30%	34%	29%	18%	26%	24%	29%	26%	33%	23%	16%
Residual risk	20%	22%	29%	19%	14%	19%	21%	23%	18%	29%	11%	
Best month	18%	31%	27%	24%	15%	26%	18%	27%	16%	36%	16%	11%
Worst month	-26%	-34%	-50%	-30%	-19%	-24%	-28%	-40%	-30%	-39%	-32%	-21%
Beta w/World	1.2	1.3	1.1	1.4	0.6	1.1	0.8	1.1	1.2	1.0	1.3	
Correlation w/World	0.70	0.69	0.54	0.77	0.58	0.68	0.52	0.63	0.74	0.50	0.87	
Normality Check												
Skewness	-0.79	-0.47	-0.97	-0.26	-0.44	-0.15	-0.43	-0.58	-0.79	-0.29	-0.96	-0.98
Kurtosis	1.30	1.65	4.22	0.92	1.12	1.06	1.22	3.51	1.19	1.89	2.83	2.39
VaR 1%	-25%	-26%	-32%	-23%	-14%	-22%	-21%	-26%	-21%	-28%	-23%	-15%
ES 1%	-25%	-29%	-39%	-26%	-16%	-23%	-24%	-32%	-25%	-33%	-27%	-18%
Tests												
Normality test (p-value)	0.0%	0.0%	0.0%	2.3%	0.4%	2.1%	0.8%	0.0%	0.0%	0.0%	0.0%	0.0%
t-test for mean	1.1	1.3	**2.0**	1.6	1.4	0.3	1.3	**2.0**	1.6	1.6	1.7	
F-test for variance	**2.9**	**3.4**	**4.4**	**3.3**	1.2	**2.6**	**2.3**	**3.2**	**2.6**	**4.3**	**2.1**	
s.e (beta)	0.09	0.10	0.14	0.09	0.07	0.09	0.10	0.11	0.08	0.14	0.06	
t-stat (beta)	**12.6**	**12.4**	**8.3**	**15.3**	**9.3**	**12.0**	**7.8**	**10.4**	**14.2**	**7.5**	**23.0**	
t-stat (correlation)	**12.6**	**12.4**	**8.3**	**15.3**	**9.3**	**12**	**7.8**	**10.4**	**14.2**	**7.5**	**23**	

7. Emerging market portfolios and backtest results

In this chapter, I present the out-of-sample performance of the backtested portfolios. The portfolios are the maximum Sharpe (MS), minimum variance (MV) and the naïve "1/n" portfolio. I have used the IR to answer my underlying hypothesis. The IR is based on the alpha and residual variance of the CAPM. In the next chapter, I have augmented the CAPM to overcome potential biases. Further, in order to see what might cause my underlying hypothesis to fail, I have estimated behavioural performances of the portfolios. In order to see any diversification benefits, I have estimated Sharpe ratios and tested for equality in variances and means. This procedure assumes that an investor would have bought and sold securities on a monthly basis over a nine-year period (2006-2014). It is assumed that an investor has the best available information on a five-year rolling window starting in 2001.

First, I will present the weight exposure of the different portfolios in the backtested sample. In table 5, we can see how the distribution of weights is divided among the countries. As we see, the active strategies discriminate among stock markets.

The MS portfolio consistently picked Colombia throughout the period. Furthermore, Peru and Chile were popular as well. However, their contribution was non-existent after 2011. Brazil contributed only slightly in the post-crisis period while Mexico contributed during the crisis. Compared with the MSCI EM Index where Asia has the highest contribution, the MS portfolio had 48% weight exposure towards Latin American stocks. For European countries, Czech Republic contributed with 13.7% of the weights, while Greece contributed by a small amount.

For the Asian region, Malaysia and the Philippines were the biggest contributors. Malaysia contributed mostly after 2009 while the Philippines contributed discontinuous throughout the period. Both China and India contributed by small amounts. My expectations were that these two emerging countries were much sought for, because of their contribution in the MSCI EM Index.

Table 5 Weight exposure to different countries over the whole backtest period.

		MS	MV
	Countries	Weight exposure	
Latin America	Brazil	1.3%	
	Chile	6.2%	11.4%
	Mexico	0.4%	2.0%
	Peru	10.7%	2.5%
	Colombia	29.7%	0.4%
Europe	Czech Republic	13.7%	4.1%
	Greece	0.1%	0.8%
	Hungary		0.1%
	Poland		
	Russia		0.8%
	Turkey		
Asia	China	0.2%	0.1%
	India	0.1%	
	Indonesia	0.4%	
	Korea		
	Malaysia	17.1%	66.5%
	Philippines	10.9%	7.4%
	Taiwan		3.0%
	Thailand	0.1%	0.2%
Africa	Egypt	9.0%	0.7%
	South Africa		
	Sum	100%	100%

The last relatively big contributor was Egypt. Its contribution existed until 2009 in the MS portfolio.

For the MV portfolio, the story is different. A big contribution attributed to Malaysia, which estimates indicates as the least risky of all EMs (figure 3). The MV portfolio seemed to recognize this. In addition, smaller weights were given to the country mates the Philippines and Taiwan.

From the Latino group Chile, Mexico and Peru had desirable properties. The portfolio weight of Chilean stocks was present in almost every month throughout the period.

European and African stocks seemed to have unappreciated exposure of what regards low risk preferences. However, Czech Republic had some contribution until the financial crisis in 2008.

Both portfolios seemed to underweight especially European stocks. As illustrated, this has been the riskiest region and has performed the poorest. Of special interest is the Latin American and Asian region. They account of almost all exposure for both portfolios.

In figure 6, I present the out-of-sample performance form the backtest of the three portfolios compared with the benchmark index. The figure illustrates what an investor would have experienced in the out-of-sample period of 2006-2014, using any of the respective strategies. The portfolios have identical base value at 100. When comparing performances I have to keep in mind my underlying research question.

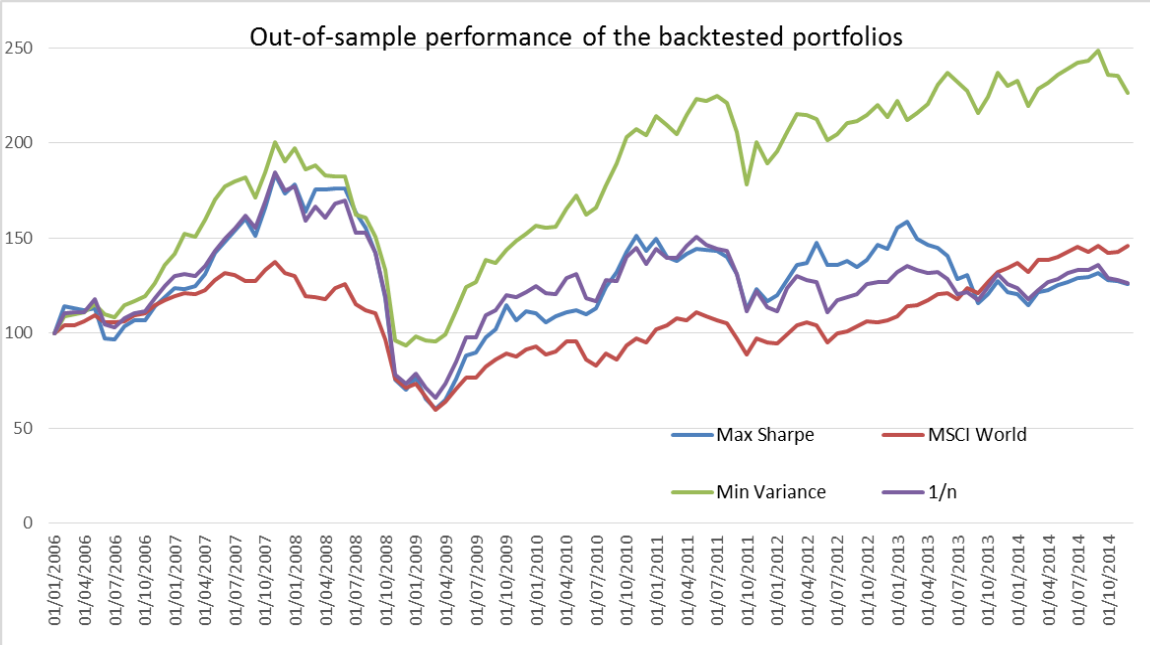

Figure 6: Out-of-sample performance of the backtested portfolios: Max Sharpe, Minimum Variance and naive (1/n) portfolio against the benchmark portfolio (MSCI World) from 2006 to 2014. Base value at 2006 = 100.

First thing to mind is the outperformance of the MV portfolio. As illustrated in figure 6, there is a momentum from the end of 2008 to the reversal in 2014. A hundred dollar invested in one share in 2006 would have translated into a wealth of \$214, without considering any fees. For the same period, a hundred dollar invested in one share in the MS portfolio, naïve portfolio, the benchmark index and MSCI EM Index would have translated into \$123, \$118, \$143 and \$126, respectively.

However, is this wealth attributable to manager skill? In table 6, I present statistics regarding the out-of-sample performance from the backtest of the portfolios over the period 2006-2014. The active investment strategies, MS, MV, respectively, did not generate a higher risk-adjusted portfolio return than the benchmark index. I see that the MV portfolio was closest, but the t-value is not large enough to reject $H0\colon IR = 0$ at the 5% level. Hence, the outperformance of the MV portfolio over the benchmark index was no more than a lucky strike. Here we see the effects of risk exposure that could be obtained in a more cost effective manner. In table 6, the betas varies and the MV portfolio have the least exposure towards the benchmark index. The beta of the MV portfolio is statistically different at the 5% level from the betas of the MS portfolio and the naïve portfolio[18]. The beta of the MV portfolio is not statistically significant different from one[19]. The opposite is true for the other two.

Table 6: Backtest statistics of the portfolios (2006-2014). Test statistics for IR, variances and means in bold are statistically significant at 5% level.

Average Annual Performance	**Max Sharpe**	**Min Variance**	**1/n**	**World**
Return	6%	10%	5%	5%
SD	25%	19%	24%	17%
Alpha	0.000	0.005	0.000	
Residual risk	15%	12%	10%	
Beta	1.2	0.9	1.3	
Sharpe	0.11	0.39	0.08	0.15
IR	0	0.14	-0.1	
t-value IR	*0.15*	*1.4*	*-0.6*	
p-value - equality in variances	***0.00***	*0.11*	***0.00***	
p-value - equality in means	*0.98*	*0.23*	*0.86*	
VaR 1%	-38%	-29%	-36%	-22%
ES 1%	-35%	-26%	-33%	-20%
Successrate bull months	76%	70%	66%	
Successrate bear months	20%	36%	28%	
No. of re-estimates	108	108		
Avg. no. of assets in portfolio	4	5	21	23
Avg. asset turnover	0.20	0.11		

A second event is the financial crisis performance of the MV portfolio. The backtest reveals that a MV portfolio was less risky in financial turmoil than a broad market index. This is consistent with the above correlation and risk comparison that events in EMs are somewhat country specific. Hence, when it is expected to be turbulence in the global financial markets, some EMs works as a safe haven, at least for this period. The test of equality in variances is satisfactory for the MV portfolio. I cannot reject that the monthly variance of the MV portfolio was different from that of the benchmark index. The opposite is true for the MS portfolio and the naïve portfolio. Since the benchmark index consist of DMs that are less risky, I see that it was possible to achieve the same result with a MV portfolio consisting of EM stocks. The reduction in risk was obtainable with an average of only five constituents. From table 6, I also see reduction in residual risk. Compared with the MSCI EM index, the residual variance is almost at the same level. Hence, expected drawdown in the MV portfolio was far less than the other EM portfolios

[18] $H0: \beta_i = \beta_j \rightarrow \ t_{\beta i} = (\beta_i - \beta_j)/(S.E_{\beta i} + S.E_{\beta j})$

[19] $H0: \beta_i = 1 \rightarrow t_{\beta i} = (\beta_i - 1)/S.E_{\beta i}$

measured by VaR and ES. Moreover, I cannot reject that the monthly returns of the MV portfolio and the benchmark index were different. However, I see that the annual average relative return was 500 bps. This implies that the MV portfolio had at least the best risk-return trade-off.

A third rather disappointing result indicated by figure 6, was the performance of the MS portfolio. The MS portfolio's out-of-sample performance was inefficient over a time horizon of 9 years. Its risk-return trade-off was weak compared to the benchmark index. Its average number of assets in portfolio was four, which indicates large exposure to few segments. With a mean annual return of 6% and a mean annual SD of 25%, its Sharpe rate was worse than that of the benchmark index. Specifically, the portfolio that in theory is the optimal risky portfolio was inefficient on the long run and the portfolios constituents seem not to compensate for the risk taken.

With a mean annual return of 5% and a mean annual SD of 24%, the naïve portfolio has the worst risk-return trade-off indicated by the Sharpe rate. It had the lowest residual risk with 21 constituents, but had the largest beta, indicating that its exposure towards the benchmark index was above average.

As the table 6 illustrates, I estimated success rates in two different market scenarios. The MS portfolio had the most success in bull markets, with a success rate of 76%. This success can be attributable to the beta of the portfolio. However, its bad performance in bear markets makes it a risky investment and inefficient on the long run. In fact, in bad months it was beaten in 80% of the time. This implies that the portfolio, indicated by the vulnerability measures, can have substantial drops. On the other hand, I can see the potential of trading in this kind of portfolio. Its success in good months in substantial. Therefore, an investor with market timing abilities could potentially gain from this portfolio.

The MV portfolio had less success in bull months compared with the MS portfolio with a success rate of 70%. However, its success in bad months is the best of the three portfolios with 36%. It has even better performance in bad months than the well-diversified naïve portfolio. At least in the sample period studied, this implies that stability and low risk attributes is a success factor when investing in EM stocks. It seems also to be an interesting finding that risk is somewhat predictable.

As illustrated in table 6, I see that the turnover for the MS and MV portfolio will reduce total wealth. Specifically, turnover is related to trading and rebalancing. I see that the MS portfolio was subject to more trading and therefore it is the most expensive.

My main objective in this chapter was to investigate whether active management is beneficial. None of the portfolios did generate a higher risk-adjusted portfolio return than the benchmark index. If the portfolios were able to generate a higher risk-adjusted portfolio return, the turnover would have affected the result. The momentum in the MV portfolio is an interesting pattern and I will see in the next chapter what might cause this movements. The out-of-sample performance of the MV portfolio did provide diversification benefits.

The optimal risky portfolio was generally inefficient. Its risk-return trade-off was not satisfactory compared to the benchmark index. Investing in this portfolio back in 2006, would have reduced total wealth compared with the MV portfolio, the benchmark index and the MSCI EM index.

The passive EM investment strategy in my sample did not have a satisfactory risk-return trade-off either. Its statistics and performance measures taken together indicates that it was an unattractive investment. A different passive weighting scheme, like replication of the MSCI EM Index, could be preferable. However, this analysis does not provide any evidence of what will happen in the future. As figure 6 indicates, the benchmark index have a momentum from 2012 until the end of the sample period. The reverse is true for EM stocks. As mentioned in the descriptive chapter, some investors may have been disappointed in the performance of EM stocks in the last few years. The question is if the performance observed by EM stocks in the most recent years will be a momentum in favour of DM stocks. In terms of risk-return trade-off, the asset pricing analysis will help to know what to expect when investing in EM stocks.

8. Emerging markets and asset-pricing models

Although the Fama-French model was invented a long time ago, the three-factor model, also extended by other researchers, is still a dominant approach for asset pricing, performance evaluation, cost of capital, etc. In the first sub-chapter, I will estimate factor betas of the backtested portfolios. In the second sub-chapter, I estimate factor betas of style portfolios representing the BRICS. If markets are integrated, there should only exist one set of risk factors. Therefore, I have assumed that the global five-factor model should be the best model to explain variation in stock returns. Thus, intercepts should be indistinguishable from zero. With my research question in mind, I will pay extra attention to the estimated intercepts and the estimated premiums.

I first investigate whether there exist size- and value effects in the sample. Figure 7 shows plots of the zero-net portfolios (RHS). There exist both size- and value anomalies local and global markets. However, on a monthly basis, this difference is minor. In terms of rational markets, the premiums on small and value stocks have not been completely arbitraged away. This implies that market participants have not detected patterns of mispricing or that they lack the ability of processing information.

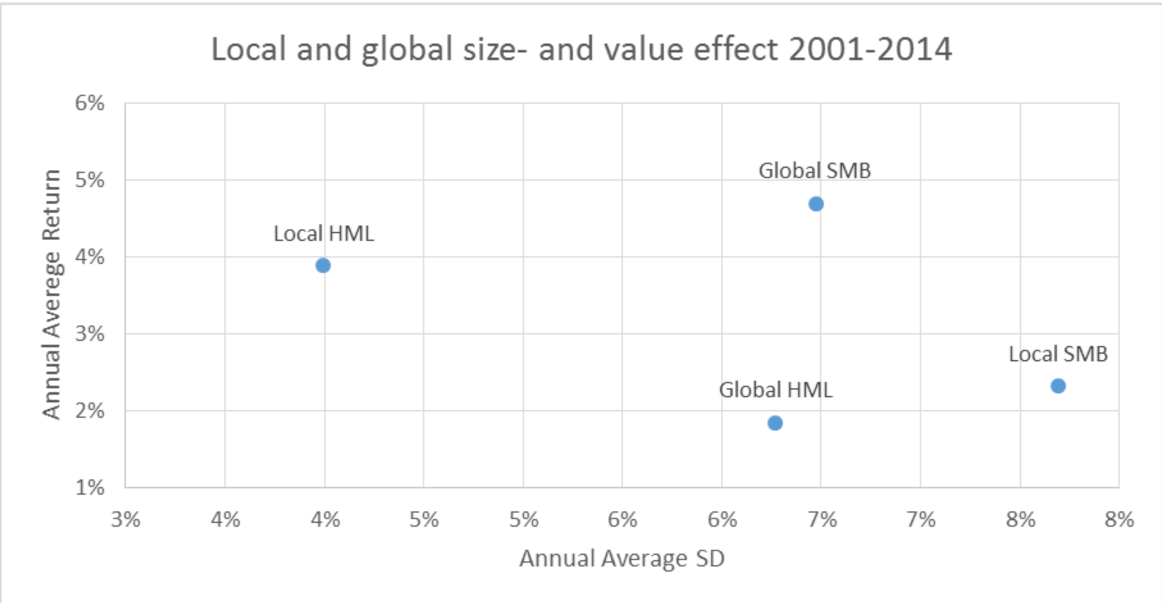

Figure 7: Local and global size and value effects in the sample period.

8.1 Asset pricing and emerging market portfolios

In this section, I will present estimation results of factor premiums of the backtested portfolios. I did not observe significant risk-adjusted returns of any of the portfolios. Because of this, my expectations is that asset-pricing models can reveal the exposure of the portfolios. This is important to investors investing in EM stocks.

My expectation is that risky stocks will have higher premiums, and that the market premium alone is insufficient in explaining return variation. According to Dyck et al. (2013), if the size premium have positive (negative) sign, it indicates that the portfolios are likely to be exposed towards small (big) stocks. Likewise, if the value premium have positive (negative) sign, the portfolios are tilted towards value (growth) stocks.

Table 7: Asset pricing with backtested portfolios in the period of 2006 – 2014.

	α	βmkt	β (local SMB)	β (local HML)	β (global SMB)	β (global HML)	R^2 adj.
Portfolios	**CAPM**						
MS	0	1.2					0.63
	(-0.1)	**(9.5)**					
MV	0	0.9					0.61
	(1.3)	**(8.2)**					
1/n	0	1.3					0.8
	(-0.4)	**(14.8)**					
	Local three-factor model						
MS	0	1.2	0.2	-0.1			0.63
	(-0.1)	**(12.9)**	(0.2)	(-0.2)			
MV	0	0.8	0.4	-0.4			0.64
	(1.3)	**(8.6)**	**(2.4)**	(-1.2)			
1/n	0	1.2	0.2	0.2			0.8
	(-0.6)	**(20.4)**	(1.7)	(0.8)			
	Global five-factor model						
MS	0	1.1	0.2	0.1	0.3	-0.3	0.63
	(-0.3)	**(11.5)**	(1.1)	(0.3)	(1)	(-0.8)	
MV	0	0.8	0.4	-0.1	0.2	-0.3	0.63
	(1.2)	**(11)**	**(2.3)**	(-0.4)	(0.9)	(-1.2)	
1/n	0	1.2	0.3	0.7	0.1	-0.5	0.81
	(-1.1)	**(19.1)**	(1.9)	**(2)**	(0.8)	**(-2.5)**	

( ) = t-values

Bold types indicates significant at 5% level

At first glance in table 7, the estimated intercepts are estimated with marginally smaller standard error for the MV portfolio when more factors are included. The opposite is true for the other two portfolios.

The market betas seem to capture strong variation in the portfolios. In fact, adding more factors increases its significance while its magnitude decreases marginally. This suggest a smaller standard error in estimating the market betas.

In the three-factor model, the magnitudes of the local size premiums are small positive and the magnitude of the local value premiums are small negative, except the value premium of the naive portfolio. The local premiums do not contribute to capture variation in the MS- and the naïve portfolio, but the local size premium is significantly related to the MV portfolio with a magnitude of 0.4. This suggest that the market beta do not capture all relevant variation in the MV portfolio. Thus, the unadjusted portfolio return of the MV portfolio is attributable to a risk premium not captured by the market beta. The sign of the local size premium signifies that the MV portfolio is tilted towards small firm stocks. However, the magnitude of the local size premium is not large and I do not know the whether small stocks would have had larger size premiums. Hence, an estimated premium of 0.4 only indicates that the stocks in the MV portfolio act similar to EM small stocks. Moreover, the R-square increases for the MV portfolio when I estimate the three-factor model.

Going from the local three-factor model to the global five-factor model, I see marginally differences regarding the MS portfolio. The market beta seems to capture relevant risk and the other premiums seem to be unrelated to this portfolio. Thus, the R-square remains at 0.63. The market premium is above average for the MS portfolio at 1.1. This suggest that the multifactor models lack the ability to identify characteristics related to return variation in the MS portfolio. As a possible inconsistency with the factor models, is that the region exposure of the MV and MS portfolios was similar. Thus, the factor models should have captured some of the same characteristics in the MV and MS portfolios. I have used an approximation of the Fama-French model that may affect the result, in addition to few observations. These characteristics may be a reason why the local factors do not explain return variation in the MS portfolio.

The local size premium has a significant positive sign in both local and global regressions regarding the MV portfolio when controlling for the other variables. The magnitude does not change and the adjusted R-square are approximately the same. The five-factor model indicates that the MV portfolio was riskier than the MS portfolio from a local perspective.

For the naive portfolio, the local size premium is marginally insignificant while the local value premium is significant at the 5% level. When I add more factors to the estimation of the naïve portfolio, the explanatory power increases marginally. Part of the reason for the higher R-square in the naïve portfolio involves less noise in this portfolio. Controlling for all variables, the local value effect is significant at the 5% level. Regarding the global premiums, the sign of the global value premium are contrary to the local value premium. From a local perspective, the portfolio is tilted towards value stocks. Form a global perspective, the portfolio is tilted towards growth stocks. The results is therefore hard to evaluate. Dyck et al. (2013) explained that funds are exposed towards different stocks by the magnitude of the premium. This suggest that the different signs of the value premiums reveal different pricing regimes of stocks worldwide. In addition, due to the significant premiums, the naïve portfolio was considered the riskiest.

Fama-French found that the magnitude of the size premium decreased from smaller to large size quantiles. Similarly, the value premium was larger in magnitude for value stocks compared with growth stocks. This is because historically, small and value stocks have been prone to more distress. Why does two of the portfolios load on the size and value factors? One can think that even these stocks contain distress risk that is not captured by the market beta. As Fama-French said, the market beta is needed to provide stocks a premium over the risk free rate. Nevertheless, in the next sub-chapter I will use the same factors on portfolios of style stocks to see the effects from another perspective.

Moreover, I have tested for functional form misspecification. I used the Ramsey RESET test i on all regressions. All regressions, except the five-factor regression of the naïve portfolio rejects the correct specification test the models at the 5% level. However, the next step is hard to decide. The portfolios have 108 observations that may be too few. Because of potential outliers, measurement error and omitted variables, the data may suffer from these biases. Instrumental variables can solve the problem but variables will be hard to detect because there is no evidence what the SMB and HML factors really are. Nevertheless, table 8 illustrates the relation between the variables in the estimation.

Table 8: Correlation matrix of the LHS- and RHS variables in the period of 2006 - 2014[20].

	Max Sharpe	*Min Var*	*1/n*	*World*	*Local SMB*	*Local HML*	*Global SMB*
Min Var	0.86						
1/n	0.92	0.90					
World	0.80	0.78	0.90				
Local SMB	0.22	0.30	0.24	0.19			
Local HML	-0.16	-0.22	-0.13	-0.17	-0.19		
Global SMB	0.40	0.41	0.42	0.40	0.27	-0.13	
Global HML	-0.02	-0.07	-0.04	0.04	0.06	0.47	-0.14

The relation between returns on large stocks and size factors are positive confirming the results. I see that there exists a negative relation between returns of large stocks and value factors. Regarding the value factors, the time series regressions should captured these movements, making me sceptical due to the positive relation between the local value effect and the naïve portfolio.

I tested the significance of the relations between the variables. The dark areas indicate statistically insignificant parameters with a 95% confidence. The local and global value factors seems to lack the relation needed to explain return variation. Due to the lack of significant correlation, I can argue that the relation between the value factors and the naïve portfolio is due to chance.

However, looking at the relation between the size factors and the portfolios, suggest that the CAPM may suffer from omitted variable bias.

8.2 Asset pricing and emerging market style portfolios

In this section, I contribute to asset pricing research in an important way. I have chosen to dig deeper in EM stocks for two main reasons. First, fund managers and investors are looking at the whole aspect of a stock market. Large- and mid-cap stocks are a major part of the financial world, but there are great potential in small firm stocks and value stocks as well. Second, if the factor models capture time series variation in stock returns it can be used to accurate pricing of stocks. However, accurate pricing depends on the degree of residual variance and alpha.

To begin, I have estimated the risk-return trade-off of the size and value portfolios representing the BRICS (LHS). In figure eight, I illustrate the relationship between four

[20] $H0: \rho = 0 \rightarrow t_\rho = \rho_i\sqrt{n-2} \Big/ \sqrt{1-\rho^2}$

equal-weighted portfolios of the five BRICS style portfolios. On average, I clearly see that independent of size, value stocks have performed best and, independent of book-to-market value, small firm stocks have been the riskiest.

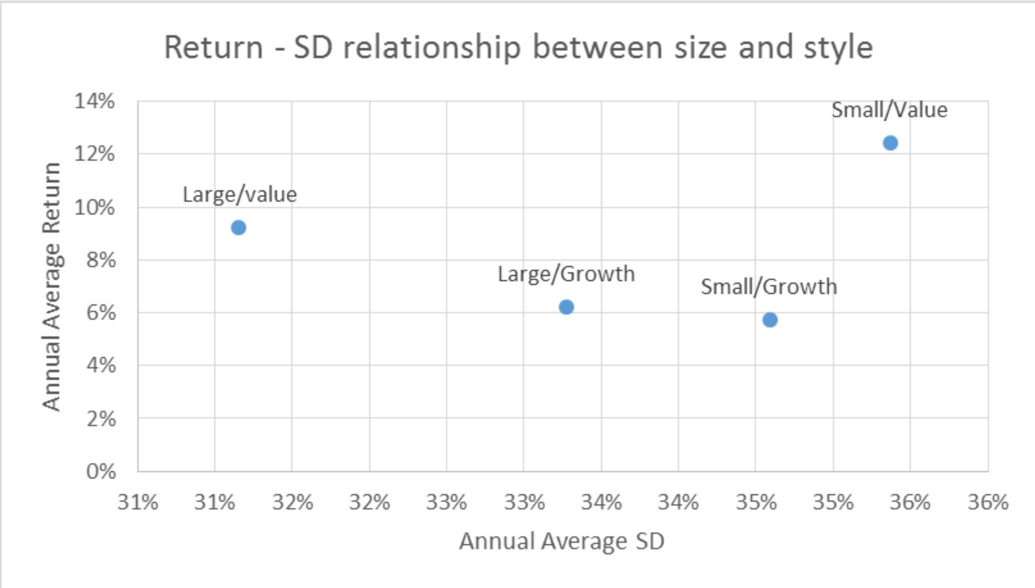

Figure 8: Returns – Standard Deviation relationship of size and value effect in the period of 2001-2014.

Figure 9 gives an illustration of the performance of the four portfolios in the period of 2001-2014.

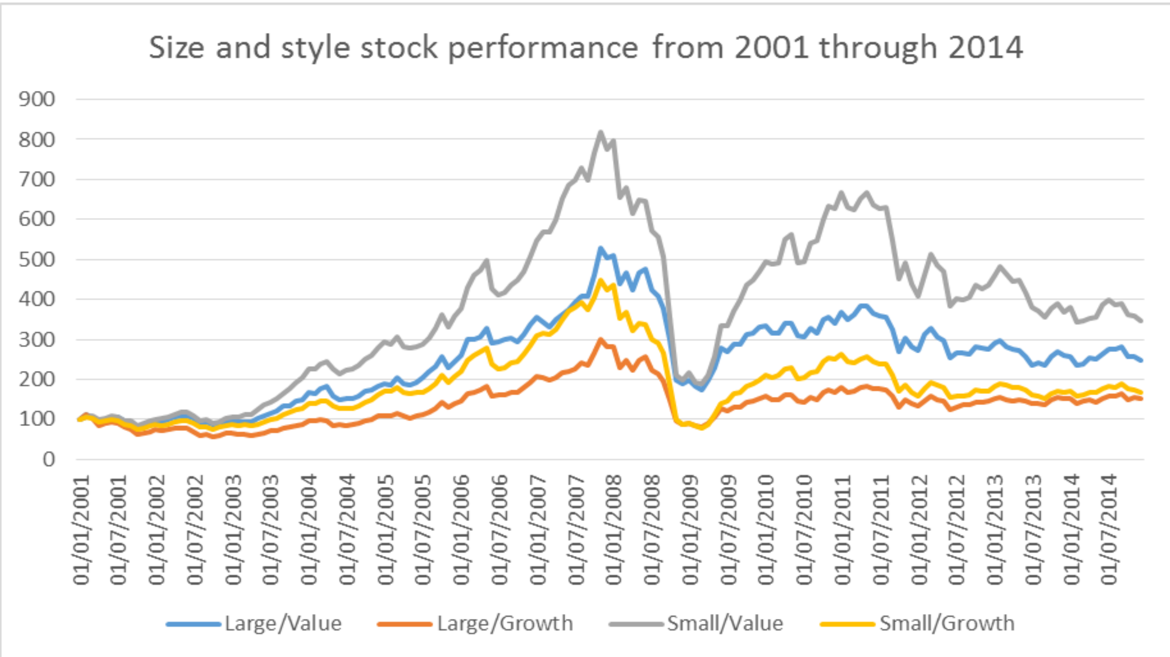

Figure 9: Performance overview of four equal weighted portfolios of size and style from the BRICS.

In table 9, I have estimated the factor premiums on large value stocks. Estimates of alpha values are statistically zero, but the alphas of Chinese and South African large value stocks are marginally insignificant. Hence, the market betas seem to capture strong variation in stock returns. However, table 9 indicates that the overall significance level of the alphas decreases, as more factors are included. This illustrates the effect of including relevant variables that cancel out anomalies. Moving to the local three-factor estimation, I see that the sign of factor exposure of the LHS variables are somewhat similar. The size premium has significant impact on large value stocks only in Brazil and India. For Brazil, the estimation is the same result as previous literature, that large firm stocks have small or negative factor exposure to the size factor. In fact, Brazilian large value stocks have negative premium on the size factor with beta equal to -1.1. However, for India the estimation indicates a significant positive size premium, though lower than average exposure. This suggest that large stocks act like small stocks and are more distressed in India. For the local value premium, Brazil, India and South Africa have significant above average exposure towards value stocks. This implies that value stocks in the respective countries are expose to distress. The value premiums of Chinese and Russian large value stocks are large positive, but insignificant.

Looking at the five-factor estimation, all models react to some extent by inclusion of more factors. Starting with Brazil, including the global size and value factors make the model predict similar results. I can see that the local factors changes marginally. The five-factor estimation for the Chinese large value stocks both the local and global value premiums are significant, but with opposite sign. From a global perspective, the estimation indicates that Chinese large growth stocks are less risky, while the opposite is true from a local perspective. For India, only the local value premium is significant. Inclusion of more variables make the local size premium suffer. Looking at Russia and South Africa, the five-factor estimation help reduce standard error and estimates significant positive local premiums and global size premiums. Overall, R-square values increase, as more factors are included in the models. Overall, the estimated global premiums have opposite sign than the local premiums. In order to give an interpretation that make sense, I will present the estimation results of the other style portfolios first.

Next, I turn to asset pricing estimation of large growth stocks.

Table 9: Asset pricing with Large/Value stocks (2001-2014).

Structure: large/value	α	β mkt	β (local SMB)	β (local HML)	β (global SMB)	β (global HML)	R^2 adj
	CAPM						
Brazil	0	1.6					0.51
	(0.5)	**(13.1)**					
China	0	1.1					0.43
	(1.7)	**(11.2)**					
India	0	1.2					0.41
	(1.4)	**(10.8)**					
Russia	0	1.4					0.44
	(0.8)	**(11.5)**					
South Arica	0	1.1					0.53
	(1.8)	**(12)**					
	Local three-factor model						
Brazil	0	1.7	-1.1	1.6			0.58
	(-0.01)	**(10.3)**	**(-4)**	**(2.7)**			
China	0	1.2	-0.2	0.7			0.44
	(1.4)	**(9.7)**	(-1)	(1.5)			
India	0	1.3	0.5	1.4			0.46
	(0.4)	**(11.6)**	**(2.1)**	**(2.8)**			
Russia	0	1.5	-0.5	0.8			0.46
	(0.5)	**(8.9)**	(-1.8)	(1.3)			
South Arica	0	1.2	-0.2	1.4			0.58
	(0.8)	**(12.7)**	(-1.2)	**(3.9)**			
	Global five-factor model						
Brazil	0	1.7	-1	2.2	0.4	-0.8	0.59
	-0.4	**(9.8)**	**(-3.4)**	**(4.1)**	(1.2)	(-1.8)	
China	0	1.1	-0.1	1.5	0.2	-0.9	0.47
	(0.8)	**(9.2)**	(-0.5)	**(3)**	(0.6)	**(-2.8)**	
India	0	1.3	0.5	1.5	0.4	-0.3	0.47
	(0.1)	**(10.3)**	(1.9)	**(2.4)**	(1.4)	(-0.7)	
Russia	0	1.4	-0.5	1.2	1.1	-0.8	0.5
	(-0.3)	**(10.4)**	**(-2)**	**(2)**	**(3.6)**	(-1.9)	
South Arica	0	1.1	-0.3	1.2	1	0	0.62
	(0.1)	**(14)**	**(-2.1)**	**(3.1)**	**(4.8)**	(0.2)	

( ) = t-values   Bold types indicate significant at 5% level

From table 10, the estimated intercepts from the CAPM are have smaller t-values, indicating that the market betas capture more variation in stock returns. However, the R-squares are only larger for Brazil and China. Considering the market betas, they seem to cancel out anomalies at least for large stocks. Brazilian large stocks seem to be highly exposed to developed markets. Market fluctuation in the developed world, especially the

US, seem to have large effect on Brazilian large stocks. In table 10, the market premiums are larger for four out of five countries compared with table 9.

Table 10: Asset pricing with Large/Growth stocks (2001-2014).

Structure: large/growth	α	β mkt	β (local SMB)	β (local HML)	β (global SMB)	β (global HML)	R^2 adj.
	CAPM						
Brazil	0	1.7					0.57
	(1)	**(12)**					
China	0	1.3					0.47
	(0.2)	**(11.5)**					
India	0	1.3					0.41
	(0.6)	**(10.9)**					
Russia	0	1.4					0.4
	(0.6)	**(10.5)**					
South Arica	0	1.2					0.47
	(0.6)	**(9.8)**					
	Local three-factor model						
Brazil	0	1.7	-0.9	0.3			0.6
	(1)	**(10.4)**	**(-3.4)**	(0.5)			
China	0	1.2	-0.3	-0.8			0.48
	(0.9)	**(12.1)**	(-1)	(-1.4)			
India	0	1.3	0.3	-0.4			0.41
	(0.8)	**(10.3)**	(1)	(-0.8)			
Russia	0	1.5	-0.3	0.8			0.41
	(0.3)	**(8.2)**	(-1)	(1.2)			
South Arica	0	1.3	-0.4	0.9			0.48
	(0.2)	**(12.3)**	(1.9)	**(2.2)**			
	Global five-factor model						
Brazil	0	1.7	-0.8	0.8	0.2	-0.6	0.61
	(0.8)	**(9.3)**	**(-2.6)**	(1.5)	(0.4)	(-1.3)	
China	0	1.3	0	0.3	-0.3	-1.1	0.52
	(0.6)	**(13.2)**	(-0.1)	(0.5)	(-0.9)	**(-3.3)**	
India	0	1.2	0.3	0.1	0.4	-0.7	0.42
	(0.3)	**(9.5)**	(1.2)	(0.2)	(1.4)	(-1.7)	
Russia	0	1.3	-0.5	0.7	1.4	-0.2	0.46
	(-0.4)	**(8)**	(-1.4)	(0.8)	**(3.8)**	(-0.3)	
South Arica	0	1.1	-0.5	1	1.3	-0.4	0.57
	(-0.8)	**(11.4)**	**(-2.6)**	**(2.2)**	**(5.6)**	(-1.4)	

( ) = t-values   Bold types indicate significant at 5% level

Looking at the three-factor model, Brazil has significant negative exposure to the size factor. The size premiums are insignificant negative for the other countries, except insignificant positive for India. The local value premium is significant positive for South

African large growth stocks. For large growth stocks to have positive exposure to the local value factor is not necessarily wrong. Compared with table 9, I see that the market and local value premiums are larger in magnitude for large value stocks. Hence, large value stocks are riskier and have higher expected return than large growth stocks in South Africa.

From the five-factor estimation, I see a rather different picture than previously. The global model have lower explanatory power on three out of five estimations. Comparing table 9 and 10, the global premiums are relatively the same. China load significant negative on the global value premium, in fact more than earlier. From a global perspective, this confirms that growth stocks are less risky than value stocks in China. For Russia and South Africa, the global size premiums are larger in magnitude and more significant than previously. This indicates that large growth stocks in Russia and South Africa act like global small stocks. However, an interesting observation is that, taken together, the premiums for South African large growth stocks indicated that these stocks are less risky than South African large value stocks.

The local factors in the five-factor estimation in table ten are not as present and I see lack of significance. Due to the sign of the premiums, BRICS large growth stocks are less risky than BRICS large value stocks. The five-factor R-squares in table 10 are lower for three out of five estimations compared with table 9.

Moreover, it will be interesting to see if small stocks exhibit different behaviour than large stocks in the following estimations.

As I saw from figure 8, small value stocks are the riskiest. This implies that these stocks should have higher factor premiums in general than for example large growth stocks. In table 11, I present asset pricing estimation of small value stocks. At a first glance, the CAPM produce a significant intercept on South African small value stocks. This implies that the market beta alone is insufficient in cancelling out anomalies. For South African small value stocks, the CAPM exhibits a lower R-square than for South African large stocks, indicating that there should exist more factors to explain return variation in South African small value stocks. The riskiness of small value stocks suggest that the CAPM could have problems in explaining return variation. As table 11 indicates, all estimated alphas have higher t-values than earlier estimates, except the alpha for Russia.

On average, the CAPM estimates lower R-square values for the style portfolios in table 11, although the betas are highly significant.

Table 11: Asset pricing with Small/Value stocks (2001-2014).

Structure: small/value	α	β mkt	β (local SMB)	β (local HML)	β (global SMB)	β (global HML)	R^2 adj.
	CAPM						
Brazil	0	1.7					0.51
	(1.5)	**(10.6)**					
China	0	1.2					0.38
	(1.7)	**(7.3)**					
India	0	1.5					0.41
	(1.5)	**(10.8)**					
Russia	0	1.7					0.37
	(0.4)	**(6.6)**					
South Arica	0.01	1.1					0.44
	(2.7)	**(11.6)**					
	Local three-factor model						
Brazil	0	1.8	0	0.8			0.52
	(0.9)	**(10.2)**	(0.3)	(1.3)			
China	0	1.2	1.2	0.7			0.47
	(0.9)	**(11.1)**	**(5.4)**	(1.6)			
India	0	1.6	1	1.5			0.48
	(0.4)	**(12)**	**(3.7)**	**(2.8)**			
Russia	0	1.8	0.5	1.2			0.39
	(-0.2)	**(6.7)**	(1.2)	(1.6)			
South Arica	0.01	1.1	0.4	1.1			0.48
	(1.6)	**(12.4)**	**(2.1)**	**(2.9)**			
	Global five-factor model						
Brazil	0	1.7	0.1	1.6	0.5	-0.9	0.54
	(0.5)	**(9.7)**	(0.3)	**(2.5)**	(1.5)	(-1.9)	
China	0	1.1	1.2	1.4	0.8	-1	0.53
	(0.2)	**(9.7)**	**(5)**	**(2.5)**	**(2.4)**	**(-2)**	
India	0	1.6	1.1	2.1	0.3	-0.7	0.5
	(0.1)	**(9.8)**	**(3.4)**	**(2.7)**	(0.8)	(-1.5)	
Russia	0	1.7	0.4	1.4	1	-0.5	0.41
	(-0.6)	**(6.6)**	(1)	(1.7)	**(2.3)**	(-0.7)	
South Arica	0	1.1	0.3	1	0.7	-0.1	0.51
	(1.1)	**(11.4)**	(1.6)	**(2.3)**	**(3.2)**	(-0.4)	

( ) = t-values   Bold types indicate significant at 5% level

Looking at the three-factor model, the significant alpha value for South Africa disappears. This implies that the detected anomaly in the CAPM is just exposure to small value stocks. Generally, the three-factor model indicates lower t-values of the intercepts for all small value estimations. The local premiums are positive and statistically significant for South African and Indian small value stocks. However, three-factor asset pricing estimation with Brazilian and Russian small value stocks are subject to large standard errors. I also see that the R-squares are marginally different. The local premiums are larger in magnitude than for large stocks estimated earlier. This is consistent with the literature on Fama and French (1993) that small- and value stocks are relatively more risky than large- and growth stocks. From table 11, the three-factor premiums for all countries implies higher expected returns. The three-factor estimation also improves the explanatory power.

Estimating the five-factor model, improves the explanatory power even more. The estimated market premiums falls slightly for three of the style portfolios, Brazil, India and Russia. This is due to the relevance of the other variables. The biggest difference in this five-factor estimation is the appearance of the local value premiums, which is significant positive for all, but not Russia. On the other hand, the global value premiums are negative for all, but only significant negative regarding China. This result is not surprising compared with large stocks, where the global value premium had a significant premium at -1.1 for Chinese large growth stocks compared with a significant premium at -1.0 in this estimation. However, the estimation indicates contrary result this time as well. Whereas the local value premiums have a positive sign, global value stocks have an inverse relationship with local value stocks.

The global size premiums are all positive, indicating that local small stocks have similar behaviour as global small stocks. However, the global size premiums were larger in magnitude for Russia and South Africa in table nine and ten.

Table 12 shows asset pricing estimation with small growth stocks. The CAPM estimation reveals a significant intercept for South African small growth stocks. The significant intercept vanish when including more factors. In general, extreme movements in small stocks seem to be up to other attributes to capture. The market premiums are in fact very similar in all estimations. The fundament of the CAPM seems to be in conflict with at least South African small stocks. The need for more power in the single factor model to explain return patterns in small stocks seem present.

Table 12: Asset pricing with Small/Growth stocks (2001-2014).

Structure: small/growth	α	β mkt	β (local SMB)	β (local HML)	β (global SMB)	β (global HML)	R^2 adj.
	CAPM						
Brazil	0	1.7					0.54
	(0.8)	**(10)**					
China	0	1.1					0.4
	(0.9)	**(10.5)**					
India	0	1.5					0.45
	(0.8)	**(8)**					
Russia	0	1.6					0.36
	(-0.3)	**(5.5)**					
South Arica	0.01	1.2					0.48
	(2.1)	**(12.4)**					
	Local three-factor model						
Brazil	0	1.7	0.1	0.1			0.54
	(0.7)	**(9.7)**	(0.3)	(0.1)			
China	0	1.1	1	-0.1			0.46
	(0.7)	**(10.7**	**(4.6)**	(0.3)			
India	0	1.5	1.1	0.5			0.51
	(0.2)	**(9.2)**	**(3.6)**	(0.9)			
Russia	0	1.7	0.8	1			0.38
	(0.9)	**(6.1)**	(1.7)	(1.4)			
South Arica	0	1.2	0.4	0.9			0.51
	(1.2)	**(13)**	**(2.2)**	**(2.3)**			
	Global five-factor model						
Brazil	0	1.6	0.1	0.6	0.7	-0.8	0.57
	(0.2)	**(9.6)**	(0.3)	(1.1)	**(2.2)**	(-1.5)	
China	0	1	1	0.5	0.8	-0.9	0.51
	(-0.1)	**(9.8)**	**(4.7)**	(1)	**(3.2)**	**(-2.7)**	
India	0	1.5	1.1	1	0.4	-0.7	0.52
	(-0.2)	**(8.7)**	**(3.7)**	(1.5)	(1.2)	(-1.7)	
Russia	0	1.6	0.5	0.6	1.4	0.2	0.42
	(-1.3)	**(6.1)**	(1.3)	(0.6)	**(2.6)**	(0.3)	
South Arica	0	1.1	0.3	1	0.9	-0.3	0.56
	(0.5)	**(12)**	(1.7)	(1.9)	**(3.6)**	(-1.1)	

( ) = t-values Bold types indicate significant at 5% level

Identical to table 11, the local premiums are significant related to small growth stocks in China, India and South Africa. For Brazilian small growth stocks, the local premiums are statistically and economically zero. I observe that the local value premiums are estimated with less standard error in table 12, compared with table 11. However, the standard error of the local value premium for Russian small growth stocks is large. In general, to conduct asset pricing estimation of Russian stocks seem complicated. In all three-factor estimations, the model has suffered. However, asset pricing for Russian stocks with the five-factor model have more explanatory power.

In the five-factor estimation in the bottom of table 12, inclusion of global factors increases R-squares for the whole group. Starting with Brazil, the market premium drops to 1.6, while the global size premium is significant positive. I observe that the significant global parameter identifies Brazilian small growth stocks as less risky than Brazilian large value stocks. The estimates of local and global size premiums are all positive, and 6 out of 10 premiums are significant positive. The estimates of all local and global value premiums are insignificant, except for a significant negative premium estimated for China.

Regarding the global value premiums, they are significant negative for Chinese style stocks in all four estimations. However, the global value premium is insignificant with a 95% confidence in all other regressions. The estimate on the global value premium varies greatly and I see large standard errors in some cases. The global size factor has positive sign in 19 out of 20 estimations. The global size premium is larger in magnitude and more often significant positive for small stocks. Regarding the local size factor, I observe premiums in line with the literature. The sign of the local size factor is positive for small stock, while the opposite is true for large stocks. The significance of the factor varied and it was estimated with large standard error especially for Russian small stocks. Regarding the local value factor, I estimated premiums in line with the literature. They are larger in magnitude regarding value stocks and several times significant positive. An interesting finding is that inclusion of the global factors works in favour of the local value factors estimated on the value portfolios.

I test for functional form misspecification with the Ramsey RESET test in this section as well. When I use the CAPM for asset pricing, I reject correct specification in three cases: Russian small value and –growth stocks and Indian small growth stocks. Regarding the three-factor model, I reject correct functional form in one case: Brazilian small growth stocks. When I estimate the five-factor model, I reject the model in four cases: Russian small value and –growth stocks, Brazilian small growth stocks and South African large growth stocks. Hence, 52 out of 60 estimations had fitting properties.

In order to see the relevance of the RHS variables, I estimated a correlation matrix. Table 13 illustrates the relation between the LHS and RHS variables. The dark areas indicates statistically insignificant relationship with a 95% confidence. First, there are no problems with multicollinearity in the models. On the other hand, the relation between the local size and value factors seem to be off in many cases. This finding indicates that the local factors may not be reliable proxies for sources of risk associated with firm size and book-to-market value. Because my local RHS variables represents the broad MSCI EM index, they could miss some important features. The global RHS variables are related with the LHS variables in several cases.

Table 13: Correlation matrix of the LHS- and RHS variables in the period of 2001-2014.

	Large/Value					***Large/Growth***				
	Brazil	*China*	*India*	*Russia*	*S-A*	*Brazil*	*China*	*India*	*Russia*	*S-A*
World	0.71	0.66	0.64	0.66	0.73	0.75	0.68	0.65	0.63	0.68
Local SMB	-0.23	-0.08	0.13	-0.12	-0.06	-0.20	-0.10	0.03	-0.08	-0.12
Local HML	-0.06	-0.09	0.01	-0.11	0.00	-0.19	-0.29	-0.22	-0.10	-0.08
Global HML	0.23	0.21	0.28	0.35	0.41	0.19	0.10	0.25	0.37	0.44
Global HML	-0.19	-0.22	-0.04	-0.21	-0.05	-0.25	-0.35	-0.23	-0.12	-0.17
	Small/Value					***Small/Growth***				
	Brazil	*China*	*India*	*Russia*	*S-A*	*Brazil*	*China*	*India*	*Russia*	*S-A*
World	0.72	0.61	0.64	0.61	0.67	0.73	0.63	0.67	0.60	0.69
Local SMB	-0.01	0.29	0.20	0.07	0.11	-0.01	0.24	0.21	0.12	0.11
Local HML	-0.11	-0.05	0.00	-0.06	-0.01	-0.19	-0.16	-0.11	-0.07	-0.05
Global HML	0.28	0.37	0.26	0.30	0.37	0.30	0.37	0.28	0.36	0.39
Global HML	-0.19	-0.12	-0.06	-0.09	-0.04	-0.22	-0.19	-0.13	-0.04	-0.08

	World	*L SMB*	*L HML*	*G SMB*
Local SMB	-0.04			
Local HML	-0.27	0.12		
Global HML	0.24	0.17	0.06	
Global HML	-0.20	0.27	0.60	0.01

In sum, the multifactor models seem to capture more variation in style stock returns than the market beta alone. The market beta struggles more to explain return variation in value stocks, as seen from the estimated t-values of the alphas. In order to capture the small firm anomaly in stocks, multifactor models are needed to get reliable results. I observe in the case of South African small stocks, the CAPM is insufficient. This is proof in favour of the Fama-French three-factor model.

I assumed that the global model should suite best to describe stock returns, because if markets are integrated, there should only exist one set of risk factors. The global five-factor model increases the R-square in all 60 estimations. However, marginally increases are observed. The global factors seem to be important in explaining return variation in EM style stocks. In 15 out of 20 regressions, the global five-factor model help reduce standard error in the estimated intercepts, compared to the three-factor model.

The contradictory results in some cases are an interesting finding. One possible explanation is that there exist different pricing regimes worldwide, where investors have different ability of handling information. Whereas local investors demand higher risk premiums of risky stocks, global investors seem to view stocks as less risky in some cases.

Fama and French (1998) find the same results as mine in a study of the value anomaly in US- and non-US markets. They estimated a model with which had described the value effect in US markets in the period of 1975-1995 before. They extended the sample to cover the years of 1987-1995. In the light of this, they assumed that world capital markets were integrated. Moreover, they found an interesting pattern in the estimation. In contradiction with their previous findings, ten of eleven sorted portfolios with low B/M (growth stocks) of smaller DMs loaded surprisingly positively on the HML factor. They further said that stocks representing these countries had a typical behaviour of value stocks. Next, they estimated the same model on EM stock portfolios. They found that value stocks and small stocks have had higher average return than growth stocks and large stocks, respectively. However, because of their short period of data and high volatility in EM stocks they did not report any asset pricing tests of EMs.

9. Main conclusions

In this thesis, I have investigated whether investments in EM stocks can generate a higher risk-adjusted portfolio return than investments in DM stocks. I used stock indices representing EM stocks to backtest portfolios and for asset pricing estimation in the period of 2001-2014. In order to investigate my underlying hypothesis, I stated the following null hypothesis: $H0: IR = 0$

In the first analysis, I backtested two assumed active portfolio strategies and one passive portfolio strategy on a monthly basis. With the use of in-sample data on a five-year rolling window, I obtained out-of-sample performance of the portfolios over a time horizon of 9 years. In order to see the risk-return trade-off, I used the MSCI World index to be the benchmark index. I used the information rate as a measure of active management success. In order to evaluate my null hypothesis, I estimated t-values of the IR. In order to investigate what might cause my underlying hypothesis to fail, I estimated behavioural measures, along with other statistics.

My assumed active portfolio strategies did not generate a higher risk-adjusted portfolio return than the benchmark index. The estimated t-values of the IR provided this evidence of a rejection with a 95% confidence. The risk-return trade-off of the Maximum Sharpe portfolios was especially disappointing. The portfolio had the most success in bull months with 76% success rate. This success did not compensate for the downside. The high beta might have caused it to fail in bull months. I observed expectations of significant drawdowns in this portfolio.

On the other hand, the Minimum Variance portfolio provided an unadjusted portfolio return to outperform the benchmark index. This was attributable to premiums on the market factor and the size factor. However, the outperformance was a lucky strike. The overall success of the portfolio attributes to more stability in bull months. I will conclude that the MV portfolio at least obtained diversification benefits. The resulting statistics of the naïve portfolio provided evidence of inefficiencies and the desire to allocate funds in other passive vehicles.

To test the validity of my underlying hypothesis, I used three different asset-pricing models in my second analysis. The purpose of asset pricing models was to reveal anomalies. In this analysis, I experimented with my backtested portfolios and a dataset containing stocks from the BRICS.

I first illustrated that there exist size and value anomalies in both EM and DM stocks. These zero-net portfolios were used as RHS variables to explain stock returns along with the market factor.

The asset-pricing estimation of the backtested portfolios provided minor new evidence of the existence of alpha. However, the asset-pricing models revealed stock return patterns that the market beta was unable to capture. Thus, the R-square increased for two of the estimations.

The asset-pricing estimation of the BRICS style portfolios illustrated that the CAPM did a poorer job than the multifactor models to cancel out size and value anomalies. In two cases, I estimated significant alphas with the CAPM. Specifically, EM small stocks and some EM large value stocks seem to have return patters in which the market beta was insufficient to explain. This is confirmed by the R-squares.

Based on my findings, investments in EM stocks are more likely to generate returns on an unadjusted basis. In the period studied, cost effective strategies like indexing would have been beneficial.

For future research, it would be interesting to investigate whether EM style stocks, such as small and value stocks, have sufficient properties to generate a higher risk-adjusted portfolio return than a benchmark index. At least for the period studied, EM small and value stocks have performed in excess of large and growth stocks, respectively. Due to this, future research should investigate investment strategies within EM spread portfolios, like the SMB and HML. This is also relevant regarding the low correlation between the spread portfolios illustrated in the bottom of table 13.

To the extent of predictability, the MV portfolio provided evidence of momentum in five consecutive years. Other researchers should take advantage of this finding and explore the issue further.

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Appendix

Table 14: Input in the MSCI World index.

North America	***Europe***	***Oseania***	***Middle-East***	***Asia***
USA	NORWAY	AUSTRALIA	ISRAEL	HONG KONG
CANADA	SWEDEN	NEW ZEALAND		JAPAN
	SWITZERLAND			SINGAPORE
	IRELAND			
	FRANCE			
	GERMANY			
	FINLAND			
	DENMARK			
	UK			
	PORTUGAL			
	AUSTRIA			
	BELGIUM			
	NETHERLANDS			
	ITALY			
	SPAIN			

Table 15: Overview of MSCI EM Index (market capitalization in million USD). Source: msci.com.

	Country	# Constituents	Market cap	Weight
Asia	China	140	767,490	19.74%
	Korea	105	566,549	14.57%
	Taiwan	101	465,016	11.96%
	India	65	269,977	6.95%
	Indonesia	30	104,031	2.68%
	Thailand	32	94,732	2.44%
	Philippines	20	47,027	1.21%
	Malaysisa	42	150,597	3.87%
Latin America	Brazil	70	401,080	10.32%
	Mexico	30	204,612	5.26%
	Chile	20	54,861	1.41%
	Colombia	14	37,738	0.97%
	Peru	3	17,233	0.44%
Middle East	Qatar	11	34,909	0.90%
	U.A.E	9	28,122	0.72%
Africa	Egypt	4	8,914	0.23%
	South Africa	51	290,961	7.48%
Europe	Russia	22	174,244	4.48%
	Poland	24	66,192	1.70%
	Turkey	25	63,589	1.64%
	Greece	10	22,897	0.59%
	Czech Republic	3	8,589	0.22%
	Hungary	3	7,975	0.21%
	MSCI EM Index	**834**	**3,887,335**	**100%**
	MSCI World Index	**1,636**	**31,426,203**	

To get an indication of what influence the index performance, we can look at table 15. Here, constituents, market capitalization and weights illustrate the contribution in the MSCI EM index. We can see that the MSCI EM index is highly exposed to Asian countries. In fact, this impact is 63.4% of the total market cap in the MSCI EM index, with China as the biggest contributor. Latin America comes in second with 18.4%. Lastly, Europe, Africa and Middle East have 8.8-, 7.7-, and 1.6% exposure respectively. We can see that it is big differences in number of constituents in the index, ranging from over a hundred to only three.

The highest sector exposure from Asian countries is information technology and financials with weights of approximately 27 % in each[21]. The next biggest contributor to MSCI EM index is Latin America. The highest sector exposure from this region is financials, consumer staples and materials with weights of 30-, 20-, and 14% respectively. Brazil has the highest weight, with its 70 constituents.

In the Middle East region, both Qatar and United Arab Emirates are highly exposed to financials, especially banks. This region has relatively low constituents.

The highest sector weights for South Africa is financials and energy with 34- and 30 % respectively. South Africa has also gained a relatively high weight in the index. Egypt, with its four constituents that represents financials and telecommunication services, has low weight.

On our last region, Europe, Russia has the highest weight. In this region, the sector exposure is highest in financials with 34.1% and energy with approximately 30%. Further, materials, consumer staples and telecommunication services have weights of 9.5-, 7.2-, and 6.6% respectively.

[21] Index fact sheets at msci.com

Table 16: Beta predictions versus actual returns based on the CAPM.

	Estimate	Actual annual (neg)	Estimate	Actual annual (pos)	Beta	Alpha
Brazil	-32%	-31%	39%	42%	1.7	0.002
Chile	-18%	-14%	22%	23%	0.9	0.004
China	-23%	-20%	28%	30%	1.2	0.004
Colombia	-19%	-10%	23%	34%	1.0	0.017
Czech Republic	-22%	-16%	27%	31%	1.1	0.008
Egypt	-20%	-12%	24%	29%	1.0	0.010
Greece	-31%	-37%	38%	27%	1.6	-0.015
Hungary	-33%	-30%	40%	35%	1.7	-0.002
India	-24%	-23%	30%	35%	1.3	0.005
Indonesia	-22%	-9%	27%	29%	1.1	0.012
Korea	-27%	-24%	33%	36%	1.4	0.006
Malaysia	-12%	-8%	15%	18%	0.6	0.006
Mexico	-23%	-20%	28%	33%	1.2	0.006
Peru	-19%	-11%	23%	31%	1.0	0.013
Philippines	-15%	-11%	18%	23%	0.8	0.007
Poland	-31%	-32%	38%	38%	1.6	-0.001
Russia	-28%	-26%	34%	35%	1.5	0.002
South Africa	-23%	-22%	28%	34%	1.2	0.006
Taiwan	-21%	-22%	25%	28%	1.1	0.001
Thailand	-21%	-13%	26%	30%	1.1	0.010
Turkey	-36%	-40%	45%	47%	1.9	-0.001
MSCI EM	-24%	-22%	30%	32%	1.3	0.004
MSCI World		-19%		23%		

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