The performance of hedge funds and mutual funds in emerging markets

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Preprint Series: 2010-01

Fakultät für Mathematik und Wirtschaftswissenschaften
UNIVERSITÄT ULM

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This version: 2010/01/12

Abstract

Use of short selling and derivatives is limited in most emerging markets because such instruments are not as readily available as they are in developed capital markets. These limitations raise questions about the value added provided by hedge funds, especially compared to traditional mutual funds active in these markets. We use five existing performance measurement models plus a new asset-style factor model to identify the return sources and the alpha generated by both types of funds. We analyze subperiods, different market environments, and structural breaks. Our results indicate that some hedge funds generate significant positive alpha, whereas most mutual funds do not outperform traditional benchmarks. We find that hedge funds are more active in shifting their asset allocation. The higher degree of freedom that hedge funds enjoy in their investment style might thus be one explanation for the differences in performance.

JEL classification: G2; G10; G11; G29

Keywords: Hedge funds; Mutual funds; Emerging markets; Performance; Asset-style factor models

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Acknowledgements: We are grateful to Benjamin A. Abugri, Christian Biener, Alexander Braun, Sandip Dutta, Christian Kraus, Przemysław Rymaszewski, Hato Schmeiser, and the participants in the 8th German Operations Research Society Workshop on Finance and Financial Institutions (Hannover, April 2009) for their valuable comments and suggestions.

1. Introduction

Institutional investors and high-net-worth individuals have put significant amounts of money into hedge funds, seeking high returns as well as diversification benefits promised by hedge fund managers (see Fung et al., 2008). Due to the absence of reliable data, academic literature on hedge funds in the 1990s was restricted to descriptive analysis and relatively simple performance metrics (e.g., Fung and Hsieh, 1997, 1999; Ackermann et al., 1999). However, as more information and data have become available, more sophisticated techniques from quantitative finance have been used to analyze hedge funds. One important stream of this literature has developed multifactor performance measurement models (Fung and Hsieh, 2001; Agarwal and Naik, 2004) that identify the sources of hedge fund returns and separate the risk premiums from different investments (beta) and the alpha that hedge fund managers provide.

Recent literature shows that classical, linear performance measurement models often cannot capture the dynamic trading strategies in the different asset classes and markets that many hedge funds pursue (Agarwal and Naik, 2004; Capocci and Hübner, 2004). Moreover, hedge funds employ a variety of trading strategies, so analyzing all hedge funds using only one performance measurement framework that does not consider the characteristics of the specific strategies is of limited value. Hedge-fund-style specific performance measurement models are needed so as to capture the differences in management style (Fung and Hsieh, 2001, 2004; Agarwal and Naik, 2004).

In this paper, we use recent innovations from performance measurement literature (Agarwal and Naik, 2004; Fung and Hsieh, 2004; Fung et al., 2008) to analyze the performance of emerging market hedge funds. We define “emerging markets” as those countries or areas of the globe that are in the process of rapid growth and industrialization, such as China, India, and Latin America, as well as many eastern European and southeastern Asian countries. These markets exhibit significant growth opportunities, but also high political and economic risks, making emerging markets more volatile than mature markets (De Santis and İmrohoroğlu, 1997). A main difference between emerging market hedge funds and other hedge funds is that use of short selling and derivatives was relatively limited in the previous two decades because such instruments were not as readily available as they are in developed capital markets.[1] These limitations raise questions about the value added provided by these funds, for example, compared to traditional long-only mutual funds.

Emerging market hedge funds have been analyzed as one among many strategies in hedge fund performance measurement literature such as Fung and Hsieh (1997, 2001), Agarwal and Naik (2004), and Capocci and Hübner (2004). However, all these authors do not analyze these funds in detail or try to extract the main differences between these funds and other hedge funds.[2] This is somewhat surprising, especially given the relative importance of emerging markets in the hedge fund industry.[3] Further the underlying factors, such as emerging market stock and bond indices, are—at least recently—more readily available than for other hedge fund strategies which involve more complex arbitrage strategies. Our analysis will show that appropriate factor models can be derived much more easily for emerging market hedge funds than for other hedge funds. Among the few authors who focus on emerging market hedge funds are Sancetta and Satchell (2004). However, they analyze only a small sample of 15 emerging market hedge funds over a relatively short period (60 months). Furthermore, their aim is to apply a new test statistic for market timing on a data sample. More recently,

[1] There is some evidence that in recent years emerging market hedge funds have had a growing set of instruments for trading in emerging markets. For example, Abugri and Dutta (2009) note that emerging market hedge funds have begun to accommodate distressed, relative value arbitrage, quantitative directional and activist strategies. Chen (2009) notes that by June 2006, 62.7% of the emerging market hedge funds in the TASS database were already using derivatives. Although this is one of the lowest values compared to other hedge fund strategies, it shows that emerging market hedge funds now face more trading opportunities and might thus have changed their strategy. This hypothesis is supported by the empirical findings of Abugri and Dutta (2009). Following Abugri and Dutta (2009), we will also analyze whether hedge funds have changed their strategy. See also Frino et al. (2009) for an analysis of derivative use in investment management.

[2] Fung and Hsieh (1997, 2001), Agarwal and Naik (2004), and Capocci and Hübner (2004) all develop performance measurement models for the whole hedge fund and funds of hedge funds market, but they do not consider emerging markets in detail.

Strömqvist (2007) analyzes the skills of emerging market hedge fund managers. Her focus is on comparing emerging market hedge funds with other hedge fund strategies, while our focus is on comparing emerging market hedge funds with mutual funds active in this market. Abugri and Dutta (2009) analyze whether emerging market hedge funds follow a pattern similar to that reported for advanced market hedge funds after 2006. The focus of this paper also differs from this analysis, in that we compare hedge funds and mutual funds active in emerging markets, while these authors analyze whether emerging market hedge funds are comparable with hedge funds that are active in advanced markets. Furthermore, we analyze individual hedge fund data; Abugri and Dutta (2009) consider hedge fund indices.[4/5]

The aim of this paper is to fill a gap in literature by providing a broad evaluation of the performance of emerging market hedge funds and mutual funds. We build upon insights from both the hedge fund and mutual fund literature and analyze six factor models, some of which are representative of recent innovations in this growing field of research. For comparison purposes, we start with the classical single-factor (1) Capital Asset Pricing Model (CAPM) and then extend our analysis to more complex multifactor models, including (2) Fama and French (1993), (3) Carhart (1997), (4) Fung and Hsieh (1997), and (5) Fung and Hsieh (2004). All these models are useful in identifying the risks underlying hedge funds and mutual funds, but they cannot account for the specific characteristics of emerging market hedge funds. We thus employ emerging market risk factors to set up our sixth model: an emerging

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3 Based on the number of funds, emerging market hedge funds are the second largest hedge fund strategy group after long/short equity (see, e.g., Capocci and Hübner, 2004; Eling, 2009).

4 In an analysis of different subperiods, we also analyze the hypotheses developed by Abugri and Dutta (2009) that since 2006 emerging market hedge funds have behaved like regular hedge funds, while traditionally before 2007) they behaved like mutual funds. Our empirical analysis of different subperiods thus extends the findings by Abugri and Dutta (2009) in that we analyze individual hedge fund data instead of hedge fund indices.

5 Another stream of literature analyzes mutual funds with a focus on emerging markets, i.e., funds that do not use leverage, derivatives, and short selling (even if such might be possible in some emerging markets). Abel and Fletcher (2004) analyzes U.K. unit trusts with a focus on emerging market equity using stochastic discount factors and finds no evidence of superior performance. Overall, the literature reports mixed findings with regard to the performance of emerging market mutual funds (see, e.g., Tkac, 2001). Aggarwal et al.

market asset class factor model. In our analysis we compare the performance of hedge funds not only with traditional benchmark indices, but also with traditional mutual funds that have an investment focus in emerging markets. Most studies only consider either hedge funds or mutual funds; we analyze both investment vehicles active in this growing market.[6]

Our analysis builds upon the Center for International Securities and Derivatives Markets (CISDM) database, which is one of the largest hedge fund databases ever analyzed for this purpose. It contains data on 566 hedge funds which have an emerging market focus. Additionally, we select 1,542 mutual funds active in emerging markets from the Thomson Financial Datastream database. The analysis covers the years 1995 through August 2008, which is advantageous for three reasons. First, the results will not suffer as much from the survivorship and backfilling biases that plague much of the older hedge fund research.[7] Second, this period contains bull as well as bear markets, allowing us to analyze the performance of emerging market hedge funds in different market environments; many other studies are limited to the analysis of bull markets.[8] Third, the analyzed time period contains some critical events for emerging market hedge funds, such as the Asian crises in 1998 and the technology bubble in 2000. We consider these events in detail in our analysis of structural breaks, subperiods, and market environments.

Our main findings can be summarized as follows. (1) Hedge fund returns and alphas are much higher than those of traditional mutual funds. (2) Some hedge funds outperform tradi-

(2007) analyze the investment allocation decision of emerging market mutual fund managers with regard to American Depositary Receipts (ADRs).

6 Chen and Chen (2009) analyze conflicts of interest with concurrent management of mutual and hedge funds for funds active in developed markets.

7 Major hedge fund data vendors did not cover dissolved funds prior to 1994. Hedge fund data before 1994 are thus not very reliable. For this reason, Capocci and Hübner (2004) decided to exclude the largest part of their hedge fund data from 1984 to 2000 in their study of hedge fund performance. For the same reason, Liang and Park (2007) start their analysis in 1995. The unreliability of data before 1994 is also discussed by Fung and Hsieh (2000), Liang (2000), and Li and Kazemi (2007).

8 See, e.g., Amenc et al. (2003), Baquero et al. (2005), and Brown et al. (1999). Although many hedge funds do not use trend-following strategies, Capocci et al. (2005) found that the market phase may influence the results. It thus seems important to have bullish as well as bearish market phases in the study. Ding and Shawky (2007) emphasizes the importance of considering different market cycles when analyzing hedge fund performance.

tional benchmarks, whereas most mutual funds tend to underperform traditional benchmarks. (3) In bad or neutral market environments, hedge funds outperform mutual funds while generating the same returns in good environments. Overall, our analysis indicates that emerging market hedge funds perform better than their traditional competitors. We also discuss potential reasons for the performance differences, i.e., higher flexibility, liquidity risk, lower regulation, and technical problems such as return smoothing.

The remainder of the paper is organized as follows. Section 2 covers the methodology, i.e., the six performance measurement models we use in the empirical part. Section 3 presents our data and discusses how we deal with the several data biases inherent in hedge fund data. In Section 4 we present our empirical findings, and we conclude in Section 5.

2. Performance measurement models

2.1. Traditional performance measurement models

For comparison purposes, we consider both classical and modern performance measurement models in our empirical analysis. The most basic performance measurement model is Jensen's alpha, based on an ex-post test of the classical CAPM:

$$R_{it}-R_{ft}=\alpha_i+\beta_i\left(R_{mt}-R_{ft}\right)+\varepsilon_{it}, \tag{1}$$

where R_{it} is the return of fund i in month t (with t=-1,-2,.., -T), R_{ft} is the risk-free return, R_{mt} the return of the market portfolio, and ε_{it} an error term. The α_i stands for the intercept of the regression and is commonly called Jensen's (1968) alpha and used as a performance measure relative to the market portfolio (see, e.g., Patro, 2001, for an application to mutual funds); the slope of the regression β_i is called the beta factor.

As the market proxy is the only factor used as a benchmark, the CAPM is a single-factor model. This single-factor modeling has been extended in literature to a multifactor framework in order to improve the portion of variance explained by the regression. We consider the Fama and French (1993) three-factor model and the Carhart (1997) model as basic multifactor specifications because they are generally not dominated by any other model in the mutual the dynamic trading strategies of hedge funds. The most prominent model of this type that has demonstrated considerable explanatory power for hedge fund returns is the factor model developed by Fung and Hsieh (2001, 2004):[9]

$$\begin{aligned} R_{it}-R_{ft} = \alpha_i + \beta_{iSNPMRF} SNPMRF_t + \beta_{iSCMLC} SCMLC_t + \beta_{iBD10RET} BD10RET_t + \beta_{iBAAMTSY} BAAMTSY_t \\ + \beta_{iPTFSBD} PTFSBD_t + \beta_{iPTFSFX} PTFSFX_t + \beta_{iPTFSCOM} PTFSCOM_t + \beta_{iMSEMKF} MSEMKF_t + \varepsilon_{it}. \end{aligned} \quad (5)$$

Fung and Hsieh employ two equity-oriented risk factors: an equity market factor, the Standard & Poor's 500 index excess returns (SNPMRF), and a size spread factor, the Russell 2000 index minus the Standard & Poor's 500 (SCMLC)[10]. Furthermore, they consider two bond-oriented factors, and three trend-following factors[11]. Recently, Fung and Hsieh added an eighth factor to this model—the MSCI Emerging Market Index (MSEMKF) (see Hsieh, 2009)—which is especially relevant in our context and therefore included in our analysis.

2.2. An asset class factor model for emerging market funds

None of the above-mentioned models captures the specific location or strategy component characteristics of investing in emerging markets. The CAPM, Fama and French (1993), and Carhart (1997) do not consider emerging market indices at all and Fung and Hsieh's models contain only one index each (the IFC emerging market index and the MSCI emerging market index). We extend these models and set up an asset class factor model for emerging market funds using various emerging market stock indices, provided by MSCI, and various emerging market bond indices, provided by JP Morgan.

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[9] One of the more recent application of this model is presented in Fung et al. (2008). Agarwal and Naik (2004), as well as Capocci and Hübner (2004), present competeting factor models that include some of the same factors as the Fung and Hsieh model considered in this paper.

[10] The original seven-factor model presented in Fung and Hsieh (2001, 2004) contains Wilshire indices, which ceased publication in December 2006. On his webpage, David Hsieh recommends using the Russell 2000 index instead (see Hsieh, 2009).

[11] The two bond-oriented factors are the change in the 10-year treasury constant maturity yield as a bond market factor (BD10RET) and the spread of the change of the Moody's Baa yield over the change of the 10-year treasury constant maturity yield as a credit spread factor (BAAMTSY). The three trend-following factors are the Bond Trend-Following Factor (PTFSBD), the Currency Trend-Following Factor (PTFSFX), and the Commodity Trend-Following Factor (PTFSCOM); see Fung and Hsieh (2001) for a detailed description of how the trend-following factors are constructed.

There are two ways to construct an asset class factor model. The first is to screen many variables through stepwise regression techniques (see, e.g., Liang, 1999, Agarwal and Naik, 2004, Vrontos et al., 2008, in a hedge fund context), which usually leads to a relatively high in-sample R^2, but to a relatively low out-of-sample R^2. The second option is to select a short list of variables that are assumed to be economically relevant. Many authors find that this approach leads to a lower in-sample R^2, but a higher out-of-sample R^2 (see, e.g., Amenc et al., 2003, in a hedge fund context). Choosing the right approach therefore involves a tradeoff between quality of fit (higher with stepwise regression, lower with economic reasoning) and robustness (lower with stepwise regression, higher with economic reasoning). In our analysis, we combine the advantages of both approaches, i.e., we present a simple-to-interpret and easy-to-use emerging market factor model and additionally discuss a stepwise regression that we implemented.

An asset class factor model should be able to explain where the hedge fund invests (the location component) and how it invests (the strategy component). To derive both of these components, we examined the fund description provided within the CISDM database for the sample of funds which we analyze. The main geographic areas in which funds are reported to be active are Asia/Pacific excluding Japan (13%), Latin America (14%), and Eastern Europe (15%). 25% report investing globally and 30% do not report their geographic focus. Regarding strategy 70% of the funds report investing in equities and 19% report investing in some kind of bonds. Only 5% report using options and 5% report using futures or forward contracts. All other instruments which are reported within the database are used more infrequently.[12] From this we infer that the most important strategies focus on equities and bonds. Re-

[12] Note that our values for use of futures and options are lower than the 62.7% reported in Chen (2009) for the TASS database. However, since reporting is not mandatory, we assume that funds are often reluctant to report all supported information fields. For example in our sample, 19% report having leveraged positions through options which is inconsistent with the low number of funds using options. For the deficiencies of hedge fund reporting, see also Fung and Hsieh (2000).

garding leverage, 22% report on average a gross leverage above 1. For those funds which reported their average gross leverage, the leverage is 1.6.

We thus designed an emerging market factor model which captures the two main investment styles of emerging market hedge funds: equities and bonds. We use three stock market indices and three bond indices to account for the different regional exposures of emerging market hedge funds. Furthermore, we include these bond indices with a lag of one month to capture possible autocorrelation effects, especially for hedge fund returns. Getmansky, Lo, and Makarov (2004) discuss possible reasons for autocorrelation in hedge fund returns and conclude that it is probably mostly attributable to illiquidity and return smoothing. We think that this effect might be more pronounced for fixed income instruments which are often not publicly listed and have no observable market price. Thus we include lagged bond indices but not lagged equity indices.

Finally, we add the credit spread factor from Fung and Hsieh's (2001, 2004) model. Fung and Hsieh (2001, 2004) argue that the credit spread is relevant with hedge funds investing in corporate bonds which are then affected by changing credit risk premiums (BAA Yield). Furthermore, they argue that hedge funds often finance their activities through lending (10-Year treasury). Given that 22% report an average gross leverage above 1, we think that this might also be the case for emerging market hedge funds. Both the direction of the bet and the financing are represented within the credit spread. Emerging market funds thus face credit risk through their investments in emerging market corporate bonds. Emerging market funds also face credit risk through their investments in emerging market governments bonds since in times of crisis there is a rush from advanced market corporate bonds and emerging market (corporate and government) bonds to safe advanced market government bonds. We thus believe that the credit spread is highly relevant for bond investors in emerging markets.[13] In summary, the model is given by:[14]

[13] Due to lack of appropriate data for emerging markets, we include the Fung and Hsieh (2001, 2004) credit spread which is constructed for advanced markets. The underlying assumption is that the advanced market

$$
\begin{aligned}
R_{it}-R_{ft} = \alpha_i &+ \beta_{iMSEMFA} MSEMFA_t + \beta_{iMSEMEA} MSEMEA_t + \beta_{iMSEFLA} MSEFLA_t \\
&+ \beta_{iJPMPASIt} JPMPASI + \beta_{iJPMPEUR} JPMPEUR_t + \beta_{iJPMPLAT} JPMPLAT_t \\
&+ \beta_{iJPMPASIL} JPMPASI_{t-1} + \beta_{iJPMPEURL} JPMPEUR_{t-1} + \beta_{iJPMPLATL} JPMPLAT_{t-1} \\
&+ \beta_{iBAAMTSY} BAAMTSY_t + \varepsilon_{it}.
\end{aligned}
\tag{6}
$$

Furthermore, we use a stepwise regression which improves the location component that we analyze on a more general level in Equation (6). We run a stepwise regression on the factors from Equation (6) and allow for a maximum of five regressors. In a second step, we improve the geographic asset allocation by replacing the remaining MSCI and JPM Morgan indices with country-level indices for the same geographic area. Again, we run a stepwise regression and allow for a maximum of five regressors.

3. Data

3.1. Data selection

We use hedge fund data provided by the Center for International Securities and Derivatives Markets (CISDM), a database frequently employed in hedge fund research (for the properties of this database, see, e.g., Edwards and Caglayan, 2001; Kouwenberg, 2003; Capocci and Hübner, 2004; Ding and Shawky, 2007; Chen and Chen, 2009). Depending on the strategy, the database can be broken down into 22 hedge fund strategies and 7 funds of funds strategies. From this database we selected the sample of those funds that are classified as emerging market hedge funds. Our initial sample consists of 566 funds with returns between January

risk factor is sufficiently highly correlated with the true emerging markets risk factor that we want to proxy. Additional tests indicate only minor variations in credit spreads among countries. In these tests we compare emerging markets credit default swap from 2004 with Moody's Baa yield less the 10-year treasury yield which are used to derive the advanced market credit spread factor in the Fung and Hsieh (2001, 2004) model. We used data on 1,273 credit default swaps for 29 emerging market countries and found that in most cases the correlation between the CDS data and the Moody´s BAA yield, less the 10-year treasury yield, is positive and highly significant. We find that 70% of all correlations are significant on a 5% level and 50% (60%) of all correlations are higher than 0.84 (0.73). The empirical connection between credit risk in advanced and emerging markets is both statistically and economically significant. The Fung and Hsieh (2001, 2004) credit spread measures credit quality differences between high-quality government bonds and low- quality corporate bonds. In times of crises there is a rush away from advanced market corporate bonds and emerging market (corporate and government) bonds to safe advanced market government bonds. Both credit risk in advanced and emerging markets thus highly depends on the state of the global economy. We thus statistically and economically see a connection between these two risk factors and believe that the advanced market credit spread factor is an appropriate proxy for credit risk in emerging markets.

[14] Note that our model (6) is comparable to the models presented by Abugri and Dutta (2009). The main difference is the inclusion of different bonds indices, lagged bond indices, and the use of the credit spread. Fur-

1995 and August 2008,[15] but our refinement of the data to minimize the biases inherent in hedge fund data, causes the loss of more than half of these funds (see below).

The mutual fund data are taken from Thomson Financial Datastream. We extracted 1,542 mutual funds that focus on emerging markets. Even though data biases are not as problematic for mutual funds, we prepare these data using the same principles as applied for the hedge funds. All following data are monthly, discrete return numbers.

Hedge funds and mutual funds are compared with passive benchmark indices. The data on the passive benchmark indices were collected from Thomson Financial Datastream, the US Federal Reserve, and the webpages of Kenneth R. French and David A. Hsieh. The equity market proxy (i.e., the market portfolio in the CAPM) is the value-weighted portfolio of all NYSE, Amex, and Nasdaq stocks used in Fama and French (1993) and Carhart (1997). The risk-free interest rate is the one-month U.S. treasury bill rate.

3.2. Data biases

Like other hedge fund databases, the CISDM database suffers from several biases, including survivorship bias, backfilling bias, selection bias, and multiperiod sampling bias. Surviving funds are those still operating and reporting whereas defunct funds have stopped reporting (Fung and Hsieh, 2000). Why funds stop reporting is difficult to discern but, quite likely, poor performance is one of the main reasons. Thus, returns of surviving funds are upward-biased. We calculated survivorship bias as the difference in fund returns between all funds and the surviving funds. This bias is 0.217 percentage points per month—a value comparable to those found in the literature (see, e.g., Fung and Hsieh 2000, 1999; Liang, 2000). For the mutual funds, survivorship bias is slightly higher at only 0.223 percentage points per month,

thermore, we do not include the Eurodollar deposit index, the spot price of gold, and the trade weighted dollar index. For example, only three of the 243 funds analyzed mention investing in gold.

[15] We follow Abugri and Dutta (2009) in that we exclude data after August 2008. They argue that an exclusion is necessary to avoid the impact of abnormal market volatility following the Lehman bankruptcy. The identical endpoint of the investigation periods allows us to empirically test the hypotheses compared by Abugri and Dutta (2009) that emerging market hedge funds have only recently begun to behave like regular hedge funds.

a trend also well documented in literature (see Liang, 2000). However, as we include both surviving and defunct funds, survivorship bias should not be a problem in this study.

When new hedge funds are added to a database, data vendors tend to backfill historical returns, which may cause another upward bias in performance, the so-called backfilling bias (also known as instant history bias). The underlying assumption is that funds have an incentive to backfill historical returns only if they have been successful in the past. Estimators for the backfilling bias can be calculated by stepwise deleting the first 12 or 24 months of returns (see Brown et al., 1999; Fung and Hsieh, 2000; Capocci and Hübner, 2004). In our sample, the monthly excess return of the portfolio that invests in all hedge funds is 0.96%. Eliminating the first 12 (24) months of returns reduces the return about 0.23% (0.23%). These values are a bit higher compared to literature (e.g., if the first 12 months are deleted Eling (2009) reports 0.18% per months and Fung and Hsieh (2000) 1.4% per year; note that for mutual funds there is no backfilling so that this bias is not relevant for this group). To adequately address the backfilling bias in our investigation, we follow Fung and Hsieh (2000) and Edwards and Caglayan (2001) and delete the first 12 monthly returns of all funds.

Since reporting to a data vendor is voluntary for hedge funds, the data might contain a selection bias. The assumption is that a manager who decides to report has a better performance than one who does not. Quantifying the selection bias would require access to returns from hedge funds that decide not to report, which are not available and thus selection bias cannot be directly addressed in a performance study. However, Fung and Hsieh (1997) argue that this bias might be limited because there also is a substantial number of well-performing funds that do not report their data because they do not want to attract new investors.

A minimum number of returns is necessary for a meaningful performance analysis, but requiring a minimum return history might create a multiperiod sampling bias (also called minimum history bias), i.e., a group of short-lived, unsuccessful funds might be eliminated. Following Fung and Hsieh (1997) and Liang (2000), we eliminate hedge funds with less than 36 monthly returns, including the 12 months deleted to address the backfilling bias. As mutual fund returns are not backfilled, we eliminate those mutual funds with less than 24 monthly returns. This reduces our sample to 243 hedge funds and 629 mutual funds. We find that our main results are not affected by the variation of the minimum number of returns and thus conclude that this bias has no substantial impact on our results.

4. Empirical results

4.1. Summary statistics

Table 1 contains descriptive statistics on the monthly return distributions of the 243 hedge funds, the 629 mutual funds, and the 26 benchmark indices; it shows the first four moments (mean, standard deviation, skewness, and kurtosis), the minimum and the maximum as well as three quantiles (25% quantile, median, 75% quantile). The last column of Table 1 provides information on autocorrelation in returns (with lag of one month). As the benchmark indices represent diversified portfolios in the various investments, we use an equally weighted average across all hedge funds and mutual funds to provide a fair basis for the comparison (as done, e.g., in Capocci and Hübner, 2004).

Hedge funds provide returns (0.96%) much higher than those of mutual funds (0.43%), but they also have a lower standard deviation (4.69% vs. 4.84%). The difference in returns also leads to much higher Sharpe ratios for the hedge funds. However, although some investors might be more concerned with central tendencies of the return distribution (mean value, standard deviation), others may care more about the distributions shape and extreme values, that is, skewness and kurtosis. We find that both hedge funds and mutual funds on average display a negative skewness with a positive kurtosis. The values are more extreme for the hedge funds, i.e., the skewness is lower and the kurtosis is much higher. This is an important finding because investors with a positive marginal utility, consistent risk aversion, and strict consistency of moment preference prefer higher values with the odd moments (mean, skewness) and lower values with the even moments (standard deviation, kurtosis) (Scott and Horvath, 1980). The negative skewness and positive kurtosis displayed by the hedge funds might thus be an unattractive combination for such investors that is not reflected by the classical Sharpe ratio or under the classical Markowitz framework (see, e.g., Moreno and Rodríguez, 2009, for a broader analysis of skewness in performance evaluation). We also use a Jarque and Bera (1987) test to check whether the observed values of skewness and excess kurtosis are consistent with the normal distribution assumption. At a 5% significance level, the rejection rate for emerging market hedge funds is 53.91% and 40.70% for the mutual funds.

	Mean	St. dev.	Skew.	Kurt.	Min.	25%	Median	75%	Max.	Autocor. (lag 1)
Hedge Funds	0.96%	4.69%	-1.46	9.88	-26.52%	-1.48%	1.80%	3.68%	14.20%	0.27
Mutual Funds	0.43%	4.84%	-1.03	5.72	-23.00%	-1.94%	1.07%	3.57%	9.96%	0.14
Market Proxy	0.45%	4.37%	-0.69	3.69	-16.20%	-2.31%	0.96%	3.50%	8.18%	0.05
SMB*	0.25%	4.01%	0.80	9.77	-16.79%	-2.21%	-0.02%	2.61%	21.96%	-0.08
HML*	0.43%	3.61%	0.08	5.47	-12.40%	-1.37%	0.33%	2.34%	13.85%	0.06
Momentum*	0.84%	5.40%	-0.56	7.07	-25.06%	-1.20%	0.87%	3.21%	18.39%	-0.08
MSCI North Am.	0.42%	4.27%	-0.48	3.38	-14.33%	-2.11%	0.85%	3.38%	9.51%	0.01
MSCI non-US	0.32%	4.19%	-0.55	3.40	-13.18%	-2.22%	0.50%	3.24%	10.12%	0.11
IFC Emerg. Markets	0.63%	6.21%	-0.82	4.44	-25.85%	-2.28%	1.11%	4.94%	12.20%	0.11
JPM US Gov. Bonds	0.20%	1.33%	-0.38	3.76	-4.75%	-0.57%	0.23%	1.06%	3.06%	0.05
JPM Non-US	0.15%	2.32%	0.30	2.84	-4.71%	-1.63%	0.03%	1.64%	6.37%	0.17
Eurodollar Deposit	-0.30%	6.78%	-0.89	8.35	-32.64%	-1.25%	0.00%	2.06%	23.19%	0.32
Gold	0.29%	4.28%	0.63	3.85	-9.38%	-2.71%	-0.04%	2.72%	16.96%	-0.01
US Dollar*	0.11%	5.00%	-0.20	3.51	-15.19%	-3.03%	0.15%	3.07%	12.17%	0.00
S&P 500	0.41%	4.23%	-0.53	3.55	-14.89%	-2.07%	0.84%	3.43%	9.31%	0.01
Size*	0.10%	3.77%	0.25	7.43	-16.38%	-2.49%	0.12%	2.50%	18.41%	-0.14
Bond*	-0.01%	0.22%	0.40	2.92	-0.53%	-0.16%	-0.04%	0.15%	0.65%	0.18
Credit*	0.01%	0.14%	0.83	4.05	-0.25%	-0.08%	-0.01%	0.06%	0.48%	0.39
TFBond*	-1.73%	13.78%	1.54	7.28	-25.36%	-10.22%	-4.15%	3.37%	68.86%	0.06
TFCur*	0.71%	17.77%	0.98	4.08	-30.00%	-11.67%	-1.97%	9.36%	66.01%	-0.01
TFCom*	0.62%	14.03%	1.31	5.82	-23.04%	-8.22%	-2.03%	7.05%	64.75%	-0.15
MSCI EM Total	0.62%	6.76%	-0.86	4.70	-29.34%	-2.81%	0.98%	5.60%	13.23%	0.08
MSCI EM Asia	0.21%	7.52%	-0.17	3.31	-19.98%	-4.55%	0.31%	5.32%	21.10%	0.21
MSCI EM EMEA	1.11%	7.49%	-0.71	4.91	-31.42%	-3.26%	2.17%	6.18%	20.55%	-0.01
MSCI EM Latin Am.	1.39%	8.13%	-0.84	4.93	-35.12%	-3.42%	2.62%	6.63%	19.90%	-0.02
JPM EM Asia	0.68%	3.03%	-2.37	24.65	-22.13%	-0.46%	0.69%	1.95%	12.94%	-0.10
JPM EM Europe	1.18%	6.36%	-4.41	41.16	-54.77%	-0.61%	1.12%	3.87%	15.96%	0.14
JPM EM Latin Am.	0.65%	4.13%	-1.64	11.74	-24.64%	-0.97%	1.13%	2.85%	11.97%	-0.13

Note: All indices are analyzed on basis of excess returns, unless indicated with an asterisk (*).

Table 1: Descriptive statistics for hedge funds, mutual funds, and passive benchmark indices

Figure 1 illustrates the risk return combinations of hedge funds, mutual funds, and most of the benchmark indices (the extreme option factors are not shown). Overall, there appears to be a positive relationship between risk and return (i.e., investments with a higher return generally have higher risk). EM hedge funds outperform most other investments. Only one of the benchmark indices (the JPM EM Asia) provides a higher Sharpe ratio than hedge funds, which again look very attractive from an investor's point of view, especially because hedge fund returns are net of all fees; passive indices, in contrast, do not include the costs of portfolio management.[16/17]

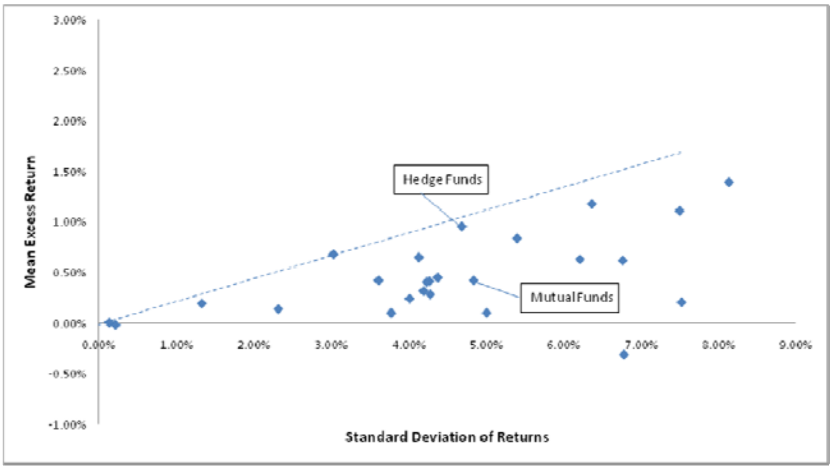

Figure 1: Risk and return combinations for hedge funds, mutual funds, and passive benchmark indices (monthly data, the three trend-following factors are not presented)

4.2. Correlation

In Table 2 we report correlation coefficients between hedge funds, mutual funds, and the passive benchmark indices. We show both the full investigation period (January 1996 to August 2008) as well as selected subperiods that we will analyze in the paper.[18]

16 The Sharpe ratio is the most widely used and best known performance measure in the investment industry (see Eling, 2008), which is why we consider it here. The Sharpe ratio, however, is only one of many performance measures and it has several deficiencies that can be addressed by alternative performance measures. For example, the classical Sharpe ratio is difficult to interpret when the excess return term in the numerator is negative (see Abugri and Dutta, 2009). Furthermore, if returns do not display a normal distribution pattern, the Cornish–Fisher expansion can be used to include skewness and kurtosis in performance measurement (see Eling and Schuhmacher, 2007). We calculated other measures such as the modified Sharpe ratio developed by Israelsen (2003, 2005), the modified Sharpe ratio developed by Gregoriou and Guyie (2003), the Sortino ratio (see Sortino and van der Maar, 1991), or the Calmar ratio (see Young, 1991). The performance comparison among these measures in presented in the Appendix. These tests show that the statement with regard to the performance of hedge funds is robust among these measures.

17 The difference in Sharpe ratio between hedge funds and mutual funds is statistically significant at 1% level. See Jobson and Korkie (1981) and the Appendix for the test results.

18 The selection of subperiods follows Fung et al. (2008) and Abugri and Dutta (2009) and will be motivated below. The correlations among the passive investment strategies are available upon request. Here we have to be careful with those indices that we use in the performance measurement model, as extremely high correlations might raise multicollinearity concerns. The correlations between indices that we use in one model, however, are all below 0.79 (and higher than -0.63) and most of them are below 0.5 which is too low to raise multicolinearity concerns. Other correlations, of course, might be higher, e.g., the correlation between the market proxy and the S&P 500 (which is 0.97), as the market proxy represents a broadly diversified U.S. stock portfolio. An analysis of the variance inflation factors (available upon request) confirms that multicolinearity is not problematic.

	January 1996 to August 2008		January 1996 to September 1998		October 1998 to March 2000		April 2000 to December 2006		January 2007 to August 2008	
	MF	HF	MF	HF	MF	HF	MF	HF	MF	HF
Hedge Funds	0.91	1.00	0.91	1.00	0.91	1.00	0.95	1.00	0.95	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mutual Funds	1.00	0.91	1.00	0.91	1.00	0.91	1.00	0.95	1.00	0.95
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Market Proxy	0.78	0.66	0.81	0.68	0.61	0.54	0.83	0.78	0.76	0.60
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
SMB	0.36	0.33	0.33	0.37	0.30	0.21	0.53	0.53	-0.26	-0.37
	(0.00)	(0.00)	(0.06)	(0.03)	(0.23)	(0.41)	(0.00)	(0.00)	(0.27)	(0.11)
HML	-0.44	-0.36	-0.50	-0.35	-0.38	-0.28	-0.45	-0.41	-0.45	-0.55
	(0.00)	(0.00)	(0.00)	(0.05)	(0.12)	(0.26)	(0.00)	(0.00)	(0.04)	(0.01)
Momentum	-0.15	-0.06	-0.15	-0.10	0.05	0.10	-0.31	-0.23	0.21	0.35
	(0.07)	(0.50)	(0.41)	(0.58)	(0.84)	(0.69)	(0.00)	(0.04)	(0.37)	(0.13)
MSCI North Am.	0.70	0.59	0.76	0.62	0.43	0.41	0.79	0.72	0.69	0.53
	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.09)	(0.00)	(0.00)	(0.00)	(0.02)
MSCI non-US	0.77	0.66	0.74	0.60	0.56	0.48	0.80	0.77	0.93	0.87
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)
IFC Emerg. Markets	0.95	0.86	0.96	0.85	0.90	0.81	0.95	0.92	0.96	0.94
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JPM US Gov. Bonds	-0.27	-0.22	-0.32	-0.35	-0.04	0.00	-0.19	-0.11	-0.60	-0.56
	(0.00)	(0.01)	(0.07)	(0.04)	(0.88)	(0.99)	(0.09)	(0.33)	(0.00)	(0.01)
JPM Non-US	-0.14	-0.13	-0.32	-0.37	-0.25	-0.28	0.00	0.10	-0.30	-0.21
	(0.08)	(0.10)	(0.07)	(0.03)	(0.32)	(0.26)	(0.97)	(0.37)	(0.20)	(0.37)
Eurodollar Deposit	0.05	0.07	-0.18	-0.04	0.21	0.36	0.03	0.00	0.08	0.08
	(0.57)	(0.39)	(0.31)	(0.84)	(0.40)	(0.14)	(0.79)	(0.99)	(0.72)	(0.73)
Gold	0.14	0.12	0.27	0.15	-0.12	-0.20	0.20	0.27	0.05	0.16
	(0.08)	(0.13)	(0.14)	(0.41)	(0.65)	(0.43)	(0.08)	(0.02)	(0.84)	(0.51)
US Dollar	0.48	0.47	0.56	0.51	0.27	0.28	0.39	0.39	0.71	0.81
	(0.00)	(0.00)	(0.00)	(0.00)	(0.28)	(0.26)	(0.00)	(0.00)	(0.00)	(0.00)
S&P 500	0.70	0.59	0.77	0.63	0.42	0.39	0.79	0.72	0.68	0.51
	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.11)	(0.00)	(0.00)	(0.00)	(0.02)
Size	0.29	0.26	0.23	0.25	0.28	0.20	0.41	0.43	-0.13	-0.25
	(0.00)	(0.00)	(0.19)	(0.17)	(0.26)	(0.42)	(0.00)	(0.00)	(0.58)	(0.28)
Bond	0.19	0.21	0.16	0.25	0.12	0.24	0.11	0.06	0.44	0.49
	(0.02)	(0.01)	(0.37)	(0.16)	(0.63)	(0.33)	(0.33)	(0.59)	(0.05)	(0.03)
Credit	-0.36	-0.38	-0.16	-0.38	-0.26	-0.30	-0.45	-0.46	-0.46	-0.48
	(0.00)	(0.00)	(0.38)	(0.03)	(0.30)	(0.22)	(0.00)	(0.00)	(0.04)	(0.03)
TFBond	-0.22	-0.27	-0.53	-0.61	-0.22	-0.03	-0.02	-0.01	-0.32	-0.31
	(0.01)	(0.00)	(0.00)	(0.00)	(0.38)	(0.90)	(0.86)	(0.94)	(0.18)	(0.18)
TFCur	-0.15	-0.09	-0.16	-0.05	-0.26	-0.33	-0.12	-0.03	-0.24	-0.28
	(0.07)	(0.26)	(0.39)	(0.78)	(0.30)	(0.18)	(0.30)	(0.78)	(0.32)	(0.23)
TFCom	-0.09	-0.08	-0.16	-0.12	-0.48	-0.42	0.01	0.08	0.13	0.03
	(0.25)	(0.31)	(0.36)	(0.52)	(0.04)	(0.09)	(0.90)	(0.49)	(0.59)	(0.92)
MSCI EM Total	0.96	0.86	0.96	0.84	0.93	0.84	0.96	0.92	0.97	0.95
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MSCI EM Asia	0.85	0.72	0.80	0.65	0.69	0.55	0.89	0.83	0.93	0.88
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
MSCI EM EMEA	0.80	0.78	0.82	0.82	0.62	0.59	0.81	0.82	0.82	0.89
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
MSCI EM Latin Am.	0.88	0.82	0.92	0.83	0.83	0.82	0.87	0.86	0.91	0.91
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JPM EM Asia	0.54	0.48	0.76	0.61	0.31	0.03	0.43	0.49	0.26	0.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.20)	(0.91)	(0.00)	(0.00)	(0.28)	(0.80)
JPM EM Europe	0.66	0.74	0.83	0.84	0.74	0.69	0.60	0.65	0.06	-0.11
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.80)	(0.64)
JPM EM Latin Am.	0.63	0.61	0.82	0.70	0.62	0.59	0.54	0.55	0.39	0.23
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.09)	(0.34)

Table 2: Correlation between mutual funds (MF) and hedge funds (HF), and passive investment strategies (p-values are given in parentheses)

With regard to the full investigation period (columns 2 and 3), the correlations between mutual funds and the stock and bond market indices are positive and significant. When considering the three emerging market stock indices and the three emerging market bond indices presented in the last six rows of Table 2, we only find significant and positive correlations. The same result is found when analyzing the correlations between hedge funds and the traditional stock and bond indices. A major argument for investing in hedge funds, however, is that the correlations with traditional investments such as stocks and bonds are somewhat lower, which makes hedge funds interesting for portfolio diversification. In fact, the correlations of the hedge fund returns with the traditional investments are generally lower than the corresponding correlation with the mutual funds. For example, the correlation between mutual funds and the S&P 500 is 0.70, but it is only 0.59 with the hedge funds.

Nevertheless, both hedge funds and mutual funds are found to be highly correlated with the returns of traditional stock and bond indices, a finding which is also quite robust among the different subperiods analyzed in Table 2. An exception, however, are the bonds indices in the most recent period (January 2007 to August 2008), where we find much lower and insignificant correlations, especially with hedge funds. For example, with the hedge funds all three JPM EM bond indices are insignificant (see last three rows in the last column of Table 2). This finding is in line with Abugri and Dutta (2009) who find significant correlations with the benchmark assets in the pre-2007 period and overwhelmingly insignificant correlations in the post-2006 period.[19]

[19] The findings by Abugri and Dutta (2009) also hold especially for bonds, while they still have positive and significant correlations with stocks in many cases. We also analyzed correlation in the subperiods at the individual fund level and found that most of the individual hedge funds exhibit much lower and often insignificant correlations with the three JPM bond indices in the most recent period. For example, while in the full sample period 60.91% (61.73%, 51.85%) of the individual hedge funds were positively and significantly correlated at 5% level with the JPM Europe index (JPM Latin America, JPM Asia), in the fourth subperiod no funds (only 6.56%, only 3.28%) were so. The findings of Abugri and Dutta (2009) with regard to differences in the post 2006 period can thus also be confirmed at the individual hedge fund level. With the individual mutual funds we also find lower correlations with the JPM bond indices, but these are less extreme.

Both for hedge funds and mutual funds, the correlation with gold, Eurodollar deposit, and the trend following factors are insignificant in most cases, while the credit spread is mostly significant. The analysis of correlation thus confirms our model design that we have based on the funds strategy description: emerging market funds exhibit credit risk. The correlation between hedge fund and mutual fund returns is 0.91. This is an interesting finding, since it illustrates that although hedge funds and mutual funds produce highly correlated returns and they tend to invest in the same asset classes, hedge funds produce a significantly higher Sharpe ratio in the full investigation period. An investigation into the underlying sources of these returns is provided in the following performance analysis.

4.3. Performance measurement results for 1996 to August 2008

Table 3 sets out the adjusted R^2 of the six performance measurement models described in Section 2. Panel A presents the results for the sample of 629 mutual funds and Panel B the results for the 243 hedge funds. Results are displayed both for an equally weighted portfolio of all funds (Column 2) as well as for the individual funds (Columns 3 to 7).

	Equally weighted portfolio	Individual funds				
		Min	25% Quantil	Median	75% Quantil	Max
	Panel A: Mutual Funds					
(1) CAPM	60.02%	-3.40%	21.98%	38.14%	50.25%	88.43%
(2) Fama and French	64.08%	-9.37%	23.65%	40.31%	52.54%	92.19%
(3) Carhart	63.86%	-13.21%	23.93%	43.07%	55.34%	91.91%
(4) Fung and Hsieh (1997)	93.10%	-19.29%	47.07%	67.58%	84.05%	95.92%
(5) Ext. Fung and Hsieh (2004)	93.52%	-28.49%	43.05%	64.97%	80.62%	98.03%
(6) EM Model	94.57%	-16.76%	53.56%	75.55%	84.76%	97.56%
	Panel B: Hedge Funds					
(1) CAPM	43.41%	-4.48%	7.99%	20.12%	31.49%	59.79%
(2) Fama and French	47.16%	-7.11%	11.05%	23.38%	34.67%	78.00%
(3) Carhart	47.15%	-9.39%	11.88%	23.64%	36.53%	79.52%
(4) Fung and Hsieh (1997)	74.76%	-28.55%	22.00%	40.62%	53.20%	93.73%
(5) Ext. Fung and Hsieh (2004)	76.35%	-21.77%	22.58%	39.85%	53.88%	87.68%
(6) EM Model	89.75%	-17.94%	31.07%	49.56%	64.96%	93.69%

Table 3: Adjusted R^2 of the performance measurement models

As expected, we find the lowest adjusted R^2 for the CAPM-based single-index model. Considering the equally weighted portfolio, the CAPM explains about 60.02% of the variation in the mutual funds returns and 43.41% of the variation in hedge fund returns. These values are comparable to other findings, e.g., Capocci and Hübner (2004) report an adjusted R^2 of 38%

in their analysis of hedge fund performance. The explanatory power is on average lower for the individual funds. For example, the median across all funds is only 38.14% for the mutual funds and 20.12% for the hedge funds. This is due to the fact that the equally weighted averages represent diversified portfolios (like the benchmark indices), whereas the individual funds are much more diverse. The adjusted R^2 of the equally weighted portfolio is better than the individual funds median for all six performance measurement models.[20]

The Fama and French (1993) and Carhart (1997) models increase the explanatory power by nearly 4% for both types of funds. Consistently, the adjusted R^2 for hedge funds is about 17% lower than that of mutual funds. The increase of approximately 4% is again in line with literature (see Capocci and Hübner, 2004). Interestingly, for the equally weighted index the Carhart (1997) model does not increase adjusted R^2 compared to the Fama and French (1993) model, i.e. the increase in explanatory power delivered by the momentum factor is not large enough to outweigh the negative impact of adding another variable to the model.

The more sophisticated multifactor models based on Fung and Hsieh (1997) and Fung and Hsieh (2004) increase the explanatory power by another 30%. The adjusted R^2 for the mutual funds is 93.10% and 93.52%, while hedge funds are again approximately 20% below that value (74.76% and 76.35%). The major reason for this increase in explanatory power is the use of an emerging market index.

This finding emphasizes the need for improved modeling of the location component with respect to different emerging stock and bond markets, which is the approach we use in our emerging market factor model. Our model is therefore able to reduce the difference in explanatory power between hedge funds and mutual funds and to capture most of the variation in hedge fund returns. The adjusted R^2 for the equally weighted portfolio of hedge funds is 89.75%. This is a very high value compared to other asset class factor models developed for

[20] An alternative to the CAPM with the market proxy (i.e. the value-weighted portfolio of all NYSE, Amex,

specific hedge fund styles. For example, Fung and Hsieh (2002) develop asset class factor models for fixed income hedge funds and find adjusted R^2 values of up to 79%. The reason for the higher explanatory power of our model might be that many hedge funds in emerging markets are long only and it thus might be easier to identify the return sources for these funds compared to fixed income funds that use complex arbitrage strategies. We also compared our results to the regression models presented by Abugri and Dutta (2009) and using our data we found an adjusted R^2 of 78.90% with their model for the composite EMHF category.[21],[22]

In Table 4 we present the alpha values for the six performance measurement models.[23] In addition to the alpha values for the equally weighted portfolio (Columns 2 and 3) and the individual funds (Columns 4 to 8), we present the percentage of funds that exhibit a significant negative (sign. < 0) and positive alpha (sign. > 0), calculated at 95% confidence level.

The mutual funds have negative alpha values in most cases, indicating that mutual fund managers on average underperform the benchmark indices. However, considering the equally weighted portfolio, none of the alpha values are significantly different from zero, except for the emerging market factor model (6). In this model, the equally weighted portfolio of the mutual funds on average underperforms the benchmark indices by 0.23%. The finding that mutual funds in emerging markets on average do not outperform traditional benchmark indices is in line with other findings in the literature (e.g., Abel and Fletcher, 2004).

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and Nasdaq stocks used in Fama and French (1993) and Carhart (1997)) is to use a broad emerging market index such as the IFC emerging market index, which results in much higher adjusted R^2.

21 We thank Benjamin A. Abugri and Sandip Dutta for helping us implement their approach. The other three models presented by Abugri and Dutta (2009) yield an adjusted R^2 of 71.12% (Asian model), 79.71% (European model), and 71.10% (Latin American model). If we use their Asian, European and Latin American index in one regression model, which would be most comparable with our model, the adjusted R^2 yields 84.98%.

22 Using stepwise regression, we find an adjusted R^2 of 87.45% for the equally weighted portfolio of mutual funds and 91.02% for the hedge fund portfolio. Compared to model (6), the stepwise regression is thus worse for the mutual funds and slightly better for the hedge funds. On an individual-fund level, however, the stepwise regression performs much better as it better fits the specific geographic and tactical exposure of the individual funds. The median adjusted R^2 for mutual funds is 78.22% and 62.17% for hedge funds. For diversified portfolios, however, the more general model (6) provides a sufficiently good approximation that cannot be improved by stepwise regression.

23 Results were determined using a heteroskedasticity and autocorrelation consistent covariance matrix (Newey and West (1987) and Andrews (1991)).

	Equally weighted portfolio		Individual funds					Alpha distribution	
	Alpha	t-stat	Min	25% Quantil	Median	75% Quantil	Max	sign. < 0	sign. > 0
	Panel A: Mutual Funds								
(1) CAPM	0.04%	0.12	-6.46%	-0.15%	0.34%	0.75%	8.27%	3.97%	14.15%
(2) Fama and French	-0.07%	-0.24	-7.86%	-0.25%	0.19%	0.65%	8.10%	3.97%	10.33%
(3) Carhart	-0.05%	-0.18	-7.28%	-0.26%	0.12%	0.46%	7.92%	3.18%	7.15%
(4) Fung and Hsieh (1997)	-0.12%	-1.08	-4.93%	-0.44%	-0.16%	0.14%	8.11%	9.86%	2.23%
(5) Ext. Fung and Hsieh (2004)	0.01%	0.06	-4.10%	-0.30%	-0.02%	0.29%	7.26%	3.18%	4.61%
(6) EM Model	-0.23%***	-2.37	-4.05%	-0.55%	-0.27%	0.01%	6.77%	14.15%	0.95%
	Panel B: Hedge Funds								
(1) CAPM	0.64%*	1.74	-5.47%	0.06%	0.48%	1.15%	3.58%	1.65%	30.45%
(2) Fama and French	0.51%	1.36	-5.78%	-0.01%	0.44%	1.03%	3.37%	2.47%	25.10%
(3) Carhart	0.45%	1.17	-5.38%	-0.12%	0.36%	0.95%	3.06%	2.47%	20.58%
(4) Fung and Hsieh (1997)	0.49%**	2.01	-5.48%	-0.18%	0.30%	0.80%	10.55%	2.88%	17.70%
(5) Ext. Fung and Hsieh (2004)	0.59%**	2.11	-5.20%	-0.02%	0.33%	1.08%	5.78%	3.29%	20.99%
(6) EM Model	0.15%	1.03	-5.98%	-0.35%	0.05%	0.57%	3.87%	5.35%	11.52%

Note: * (**, ***) indicates significance at 10% (5%, 1%) level.

Table 4: Alpha of the performance measurement models

This situation might be different for hedge funds, as the few fund managers who have beaten passive strategies tend to move to alternative investments and start their own hedge fund (see Agarwal and Naik, 2000). In contrast to the mutual funds, hedge funds have positive alpha values and two of them are statistically significant on a 5% level (with the Fung and Hsieh (1997) model and the ext. Fung and Hsieh (2004) model). For all models except model (5), the percentage of hedge funds exhibiting underperformance (sign. < 0) is lower than that of mutual funds and the percentage of hedge funds outperforming (sign. > 0) is higher for all models than for mutual funds, indicating that hedge fund managers on average perform better than mutual fund managers. Using the CAPM, 30.45% of all hedge funds outperform the benchmark, while with the EM factor model only 11.52% have a superior performance. With the EM factor model, only 0.95% of the mutual funds outperform the traditional benchmark indices, while 14.15% provide a significantly lower performance.[24]

In Table 5 we show regression results for the equally weighted portfolios of mutual funds and hedge funds. While for both mutual funds and hedge funds the equity factors are significant, this is not the case for the bond factors for Latin America and Asia. The intercept (i.e., alpha) is significant and negative for mutual funds while it is positive but insignificant for hedge funds. The credit spread is significant and negative for both hedge funds and mutual funds.

[24] With the stepwise regression, the results are mostly more extreme, i.e., both the number of funds with a significant positive alpha and those with a significant negative alpha are higher than with model (6). For example, with model (6), 35.18% percent of all mutual funds have a negative alpha on a 5% significance level.

The negative sign of the credit spread can be interpreted as follows: As the yield of low quality bonds rises faster than the yield of 10-year US treasuries (i.e. credit risk increases), returns of the funds are negatively affected because the low-quality bonds in which funds are invested lose value.

	Mutual Funds estimator	t-stat	Hedge Funds estimator	t-stat
Intercept	-0.0023**	(-2.375)	0.0015	(1.034)
MSCI EM Asia	0.267***	(13.421)	0.1261***	(4.953)
MSCI EM Europe	0.1446***	(7.456)	0.1331***	(4.138)
MSCI EM Latin Am.	0.1637***	(6.782)	0.1905***	(5.692)
JPM EM Latin Am.	0.0786	(1.618)	0.0028	(0.045)
JPM EM Asia	0.0644	(1.179)	-0.0519	(-0.784)
JPM EM Europe	0.088***	(2.946)	0.2519***	(7.282)
JPM EM Latin Am. t-1	0.0397	(1.201)	0.0439	(1.062)
JPM EM Asia t-1	-0.0574	(-1.303)	-0.0603	(-1.009)
JPM EM Europe t-1	0.0408*	(1.750)	0.1257***	(3.787)
Credit Spread	-3.129***	(-4.470)	-3.5042***	(-3.799)

Note: * (**, ***) indicates significance at 10% (5%, 1%) level.

Table 5: Regression result for mutual funds and hedge funds with EM model (6)

4.4. Performance measurement results for different subperiods

In Table 6 we present the results for different subperiods in an effort to test the robustness of our results over time. The selection of subperiods is motivated by two recent studies (Fung et al., 2008; Abugri and Dutta, 2009) which allows us to analyze the impact of two highly relevant events (Asian crisis, peak of the technology bubble; Fung et al., 2008) as well as to analyze whether a recent style shift in hedge fund behavior has occurred (Abugri and Dutta, 2009). We thus subdivide the sample period of 1996 to August 2008 into four subperiods. For the first three periods we follow Fung et al. (2008) in how we subdivide the sample: the Asian crises (January 1996 to September 1998), the time after the Asian crises until the peak of the technology bubble (October 1998 to March 2000), and the time after the peak of the technology bubble (April 2000 to December 2006). The selection of the last period is motivated by Abugri and Dutta (2009) and spans from January 2007 to August 2008. Abugri and Dutta (2009) find that emerging market hedge funds have followed a pattern similar to that reported for advanced market hedge funds only in the most recent period, from January 2007 to August 2008, while before that time they behaved like regular mutual funds.

	Eq. w. portfolio		Individual funds					Alpha distribution	
	Alpha	t-stat	Min	25%	50%	75%	Max	sign. < 0	sign. > 0
Subperiod: January 1996 to September 1998									
	Panel A: Mutual Funds								
(1) CAPM	-2.06%***	-2.90	-7.74%	-3.02%	-2.42%	-1.13%	0.34%	49.62%	0.00%
(2) Fama and French	-1.95%***	-2.97	-8.87%	-3.00%	-2.29%	-1.03%	1.00%	45.80%	0.00%
(3) Carhart	-1.84%**	-2.40	-7.82%	-2.86%	-2.26%	-1.01%	1.00%	35.88%	0.00%
(4) Fung and Hsieh (1997)	-0.09%	-0.25	-4.93%	-0.48%	0.02%	0.51%	2.76%	5.34%	2.29%
(5) Ext. Fung and Hsieh (2004)	0.23%	0.66	-4.26%	-0.31%	0.35%	0.96%	5.13%	3.82%	12.98%
(6) EM Model	-0.36%	-1.41	-3.91%	-0.85%	-0.44%	0.08%	2.44%	17.56%	0.76%
	Panel B: Hedge Funds								
(1) CAPM	-1.27%	-1.05	-5.12%	-2.61%	-1.24%	-0.17%	1.81%	19.23%	1.92%
(2) Fama and French	-1.24%	-1.15	-4.21%	-2.64%	-1.39%	-0.15%	2.34%	15.38%	1.92%
(3) Carhart	-1.35%	-1.14	-4.44%	-2.67%	-1.32%	-0.28%	1.94%	11.54%	1.92%
(4) Fung and Hsieh (1997)	0.89%	1.23	-1.95%	-0.19%	0.86%	1.61%	10.55%	0.00%	15.38%
(5) Ext. Fung and Hsieh (2004)	2.05%***	3.28	-2.50%	0.36%	1.48%	3.47%	7.42%	0.00%	30.77%
(6) EM Model	0.44%	0.81	-2.90%	-0.55%	0.09%	0.80%	3.87%	5.77%	7.69%
Subperiod: October 1998 to March 2000									
	Panel A: Mutual Funds								
(1) CAPM	1.51%**	2.16	-2.92%	0.76%	1.43%	2.05%	7.75%	0.56%	15.56%
(2) Fama and French	1.46%*	2.02	-3.75%	0.77%	1.33%	2.04%	6.53%	0.56%	15.56%
(3) Carhart	1.46%**	2.48	-3.75%	0.75%	1.35%	2.04%	6.53%	0.56%	19.44%
(4) Fung and Hsieh (1997)	0.06%	0.31	-5.43%	-0.74%	-0.16%	0.55%	5.46%	11.67%	5.56%
(5) Ext. Fung and Hsieh (2004)	0.81%	1.58	-10.57%	-0.29%	0.57%	1.74%	9.44%	0.56%	9.44%
(6) EM Model	-0.46%*	-2.06	-10.30%	-1.22%	-0.60%	0.22%	5.02%	8.33%	1.11%
	Panel B: Hedge Funds								
(1) CAPM	2.14%**	2.60	-4.02%	0.72%	2.05%	3.20%	7.83%	1.30%	23.38%
(2) Fama and French	2.20%**	2.69	-4.11%	0.73%	2.38%	3.25%	8.78%	1.30%	24.68%
(3) Carhart	2.20%**	2.62	-4.11%	0.73%	2.39%	3.25%	8.78%	1.30%	27.27%
(4) Fung and Hsieh (1997)	0.93%	1.26	-6.60%	-0.35%	0.63%	1.74%	7.57%	1.30%	11.69%
(5) Ext. Fung and Hsieh (2004)	0.87%*	1.90	-9.24%	-0.67%	0.55%	2.00%	9.02%	1.30%	9.09%
(6) EM Model	-0.25%	-0.48	-7.14%	-2.00%	-0.41%	0.97%	5.63%	3.90%	3.90%
Subperiod: April 2000 to December 2006									
	Panel A: Mutual Funds								
(1) CAPM	0.57%**	2.10	-1.57%	0.21%	0.59%	0.97%	9.39%	1.28%	22.91%
(2) Fama and French	0.26%	0.92	-2.68%	-0.17%	0.20%	0.52%	9.38%	2.57%	6.85%
(3) Carhart	0.24%	0.88	-2.29%	-0.15%	0.22%	0.56%	9.37%	2.78%	7.07%
(4) Fung and Hsieh (1997)	-0.12%	-0.96	-2.99%	-0.54%	-0.17%	0.17%	8.94%	10.49%	2.36%
(5) Ext. Fung and Hsieh (2004)	-0.06%	-0.39	-2.39%	-0.42%	-0.05%	0.25%	10.28%	3.64%	3.64%
(6) EM Model	-0.30%*	-1.88	-5.04%	-0.61%	-0.26%	0.03%	8.56%	9.85%	1.07%
	Panel B: Hedge Funds								
(1) CAPM	1.07%***	4.18	-7.54%	0.45%	0.84%	1.60%	4.49%	0.59%	48.82%
(2) Fama and French	0.78%***	3.27	-9.87%	0.16%	0.50%	1.21%	4.80%	1.76%	34.12%
(3) Carhart	0.79%***	3.22	-10.27%	0.17%	0.51%	1.24%	4.73%	1.76%	33.53%
(4) Fung and Hsieh (1997)	0.46%***	2.92	-7.56%	0.00%	0.43%	1.00%	4.59%	2.94%	27.65%
(5) Ext. Fung and Hsieh (2004)	0.57%***	3.50	-9.07%	0.06%	0.45%	1.15%	4.22%	1.76%	31.76%
(6) EM Model	0.05%	0.28	-11.90%	-0.35%	0.16%	0.58%	2.99%	5.88%	10.00%
Subperiod: January 2007 to August 2008									
	Panel A: Mutual Funds								
(1) CAPM	0.21%	0.35	-2.16%	-0.14%	0.20%	0.65%	4.71%	1.76%	2.93%
(2) Fama and French	0.04%	0.08	-2.30%	-0.31%	0.07%	0.44%	4.37%	2.93%	4.11%
(3) Carhart	-0.13%	-0.28	-2.33%	-0.38%	-0.09%	0.22%	4.14%	3.23%	2.35%
(4) Fung and Hsieh (1997)	-0.20%	-1.02	-2.70%	-0.53%	-0.19%	0.19%	3.92%	10.85%	2.35%
(5) Ext. Fung and Hsieh (2004)	-0.18%	-1.18	-2.81%	-0.55%	-0.26%	0.17%	4.18%	7.33%	2.05%
(6) EM Model	-0.04%	-0.18	-4.94%	-0.35%	-0.02%	0.37%	6.05%	5.87%	2.64%
	Panel B: Hedge Funds								
(1) CAPM	0.18%	0.31	-2.25%	-0.13%	0.21%	0.58%	3.68%	1.64%	7.38%
(2) Fama and French	-0.01%	-0.03	-3.18%	-0.39%	0.09%	0.51%	3.30%	4.10%	9.02%
(3) Carhart	-0.20%	-0.41	-4.15%	-0.62%	-0.05%	0.40%	3.43%	5.74%	6.56%
(4) Fung and Hsieh (1997)	0.04%	0.20	-2.53%	-0.38%	0.11%	0.55%	2.88%	4.10%	7.38%
(5) Ext. Fung and Hsieh (2004)	0.05%	0.17	-2.96%	-0.45%	0.15%	0.59%	3.82%	0.82%	9.84%
(6) EM Model	-0.12%	-0.27	-3.67%	-0.64%	0.03%	0.43%	2.55%	1.64%	5.74%

Note: * (**, ***) indicates significance at 10% (5%, 1%) level.

Table 6: Alpha of the performance measurement models in different subperiods

Table 6 confirms the above finding that hedge funds on average have better performance than mutual funds. For both the equally weighted portfolio (Eq. w.) and the individual funds (Median, Sign. < 0, Sign. > 0), hedge funds perform better in nearly all subperiods and for all models. An interesting finding in model (5), the extended Fung and Hsieh (2004) model, is that emerging market hedge funds significantly outperform the benchmark indices both in the second subperiod (1998 to 2000), the time after the Asian crises, and in the third subperiod (2000 to 2006). Using a comparable model and considering funds of hedge funds, Fung et al. (2008) find that these outperform the market only during the small time window between 1998 and 2000, while at the end of their investigation period alphas of hedge funds decline. While in model (5) the absolute value of alpha declines in the third period (from 0.87% to 0.57%), the significance becomes even stronger. In contrast to Fung et al. (2008), however, Strömqvist (2007) identifies an upward trend in the performance of emerging market hedge funds over time and concludes that emerging market funds might be where future alphas can be found. We cannot confirm either an upward or a downward trend in alphas here, especially since in the emerging market model (6) the results for hedge funds are insignificant for the second and the third subperiods. Note, however, that in model (6) the mutual funds significantly underperform in both these periods. In the fourth period, results are insignificant both for hedge funds and mutual funds. Later results from a rolling regression will help to shed more light on the development of alpha over time and these are more in line with Strömqvist (2007).

Table 7 shows the regression results for the equally weighted portfolio in the different subperiods. For the mutual funds, all of the equity indices are significant except for one index in one subperiod. For the hedge funds the picture is different. The equity factors are often not significant. Only from April 2000 to December 2006 are all of them significant. One problem here could be the relative brevity of the other subperiods. Another possible explanation is that funds performance literature (see Capocci and Hübner, 2004). The Fama and French (1993) model has two additional factors, one for size (SMB, i.e., small minus big) and one for the ratio of book-to-market value (HML, i.e., high minus low book-to-price ratio):

$$R_{it}\text{-}R_{ft}=\alpha_i+\beta_{im}\left(R_{mt}\text{-}R_{ft}\right)+\beta_{iSMB}SMB_t+\beta_{iHML}HML_t+\varepsilon_{it}\,. \tag{2}$$

Carhart (1997) adds a momentum (MOM) factor to the Fama and French (1993) model, which accounts for trend-following strategies in stock markets, i.e., buying stocks that were past winners and selling past losers:

$$R_{it}\text{-}R_{ft}=\alpha_i+\beta_{im}\left(R_{mt}\text{-}R_{ft}\right)+\beta_{iSMB}SMB_t+\beta_{iHML}HML_t+\beta_{iMOM}MOM_t+\varepsilon_{it}\,. \tag{3}$$

Many empirical implementations (e.g., Fama and French, 1993) use diversified portfolios of stocks as a proxy for the market portfolio. The first three models thus focus primarily on stock markets. However, hedge funds are flexible enough to select from among many asset classes and can employ dynamic trading strategies. Accordingly, these three models have been extended to capture alternative asset classes as well as to accommodate differences between the approach used by hedge fund managers as compared to the strategies engaged in by traditional mutual fund managers (see Fung and Hsieh, 1997). Fung and Hsieh (1997) define eight standard asset classes useful for analyzing fund performance—three equity indices (MSCI North American (MSUSAM), MSCI non-US (MSWXUS), IFC Emerging Markets (IFCOMP)), two bond indices (JP Morgan US Government Bonds (USMGUSRI), JP Morgan Non-US Government Bonds (USMGEXRI)), currencies (Federal Reserve Traded Weighted Index of the US Dollar (USD)), the one-month Eurodollar Deposit Return of the previous month (ECUSD1M), and gold (GOLDBLN; London morning fixing):

$$\begin{aligned}R_{it}\text{-}R_{ft}=\alpha_i&+\beta_{iMSUSAM}MSUSAM_t+\beta_{iMSWXUS}MSWXUS_t+\beta_{iIFCOMP}IFCOMP_t\\&+\beta_{iUSMGUSRI}USMGUSRI_t+\beta_{iUSMGEXRI}USMGEXRI_t+\beta_{iUSD}USD_t\\&+\beta_{iECUSD1M}ECUSD1M_{t\text{-}1}+\beta_{iGOLDBLN}GOLDBLN_t+\varepsilon_{it}\,.\end{aligned} \tag{4}$$

The eight standard asset classes used in Fung and Hsieh (1997) can capture the different asset classes used by hedge funds and mutual funds, but option-like factors are needed to capture hedge funds in fact have different asset allocations during these periods. With regard to the last period, this interpretation would be in line with Abugri and Dutta (2009) who find a change in the behavior of hedge funds after 2006.

To investigate these changing hedge fund patterns, we look at the individual fund level. We find more often a significant exposure towards the JPM EM Bond indices if we compare the complete period from January 1996 to August 2008 to the period from January 2007 to August 2008. On a 5% level and during the whole investigation period, 11.93% of all funds have a significant exposure toward the JPM EM Latin America, 9.88% toward the JPM EM Asia, and 27.98% toward JPM EM Europe. During the post-2006 period, the respective numbers are 7.38%, 9.02%, and 10.66%. For the MSCI EM equity indices, the percentage of funds with significant exposure toward the MSCI EM EMEA or Asia does not decrease substantially. For the MSCI EM Latin America, however, the percentage decreases from 24.28% to 8.20%. These results partly confirm the findings from the correlation analysis as well as those from Abugri and Dutta (2009).

	January 1996 to September 1998		October 1998 to March 2000		April 2000 to December 2006		January 2007 to August 2008	
	MF	HF	MF	HF	MF	HF	MF	HF
Intercept	-0.0036	0.0044	-0.0046*	-0.0025	-0.003*	0.0005	-0.0004	-0.0012
	(-1.407)	(0.815)	(-2.06)	(-0.481)	(-1.878)	(0.279)	(-0.185)	(-0.265)
MSCI EM Asia	0.2607***	0.2278**	0.1043***	0.1365**	0.3043***	0.1233***	0.2836***	0.1789**
	(4.889)	(2.627)	(3.826)	(2.591)	(8.476)	(4.536)	(7.913)	(2.3)
MSCI EM EMEA	0.1466***	0.1302	0.1322***	0.192	0.1453***	0.1195***	0.0999***	0.164*
	(4.648)	(1.482)	(7.305)	(1.651)	(5.96)	(5.03)	(5.617)	(2.111)
MSCI EM Latin Am.	0.1298	0.2606	0.1906**	0.1151	0.1492***	0.1474***	0.1215**	0.1302
	(1.654)	(1.615)	(2.996)	(1.085)	(4.1)	(4.206)	(2.978)	(1.534)
JPM EM Latin Am.	0.3494**	0.0068	0.0325	0.3737*	0.0241	-0.0265	0.1489	-0.0447
	(2.732)	(0.025)	(0.237)	(2.259)	(0.449)	(-0.509)	(1.084)	(-0.162)
JPM EM Asia	0.024	-0.0853	0.4882***	-0.334	0.0847	0.1827**	0.289**	-0.1247
	(0.156)	(-0.274)	(4.075)	(-1.305)	(0.956)	(2.27)	(3.045)	(-0.576)
JPM EM Europe	-0.0247	0.1424	0.2153***	0.2802**	0.1828***	0.2222***	-0.1204	0.0449
	(-0.354)	(1.374)	(9.259)	(3.168)	(2.698)	(3.547)	(-0.48)	(0.189)
JPM EM Latin Am. t-1	0.0765	0.4188*	0.0778**	-0.0256	0.0745	0.0402	-0.3395**	-0.1567
	(0.543)	(1.822)	(2.461)	(-0.164)	(1.535)	(1.176)	(-2.796)	(-0.494)
JPM EM Asia t-1	-0.0044	-0.6296**	-0.2537***	0.0182	-0.1176	0.1039	-0.1474	-0.0325
	(-0.021)	(-2.127)	(-4.219)	(0.087)	(-1.362)	(1.252)	(-1.127)	(-0.122)
JPM EM Europe t-1	0.0511	0.1437	0.0825**	0.1219	0.0158	0.0258	0.8425***	0.2677
	(0.74)	(1.084)	(3.274)	(1.412)	(0.284)	(0.57)	(4.432)	(0.583)
Credit Spread	-2.1687	-11.6257	-6.4662***	-6.0499	-2.2353	-3.6225***	-5.8539***	-2.3937
	(-0.573)	(-1.301)	(-4.36)	(-1.45)	(-1.632)	(-3.901)	(-23.405)	(-1.368)

Note: * (**, ***) indicates significance at 10% (5%, 1%) level.

Table 7: Regression result for mutual funds (MF) and hedge funds (HF) with EM model (6) in subperiods

In order to analyze extreme market events and changing return patterns more closely, we follow Fung and Hsieh (2004) and Fung et al. (2008) and use a modified CUSUM test to find structural breakpoints in factor loadings (see Meligkotsidou and Vrontos (2008) for a more detailed analysis of structural breaks in hedge fund returns). Fung and Hsieh (2004) as well as Fung et al. (2008) find that structural breaks coincide with extreme market events (in their case the collapse of Long-Term Capital Management in September 1998 and the peak of the technology bubble in March 2000) and conclude that these events might affect managers' risk-taking behavior. Our findings here are mixed. Using a Rec-CUSUM and an OLS-Cusum test we find a breakpoint on a significance level of at least 10% for neither hedge funds nor mutual funds at the level of the equally weighted portfolio. We also use the Chow test to test for structural breaks with regard to the different dates. Here we find significant breakpoints in October 1998 and April 2000 but not in January 2007 for hedge funds. For mutual funds, all tests reject the existence of breakpoints. On an individual-fund level we test for breakpoints using a Rec-CUSUM and an OLS-CUSUM test. Significant breakpoints are found for mutual funds in 5.76% (9.47%) of all cases and for hedge funds in 2.85% (5.23%) cases with a Rec-CUSUM (OLS-CUSUM) and a 95% confidence interval. Overall, the results are not clear and depend on the test that is used. Given that we find significant structural breaks using the Chow test in October 1998 and April 2000 for hedge funds but not for mutual funds supports the idea that hedge funds adapt to changing market environments while mutual funds do not.

Figures 2 a) to c) show rolling regressions using model (6) with a 36-month time window that examines a manager's exposures to the MSCI EM Asia, the MSCI EM Latin America, and the MSCI EM EMEA, i.e. the estimated regression coefficient and a 90% confidence interval over time.[25] The upper (middle) part of the figure presents the analysis for the equally weighted mutual (hedge) fund portfolio. The bottom presents the returns of the respective MSCI EM index in the time period under consideration.

In Figure 2 a) we see that the exposure of hedge funds towards the Asian market declines from mid-1997 to mid-2000. For the mutual funds this effect is weaker. Figure 2a) also shows that from 1999 to 2002, mutual funds increased their exposure to the Asian markets while hedge funds kept their exposure low. Exactly during this time, the MSCI EM Asia has negative returns. After this period, we see a rise in the exposure of hedge funds towards the Asian market, a time which was followed by positive returns with the MSCI EM Asia index. All these shifts in exposure suggest the good timing abilities of hedge fund managers.

Regarding the exposure to the MSCI EM Latin America index (Figure 2 b) the interpretations are vague since the confidence band is broader than for the other indices. In general, however, both hedge funds and mutual funds reduced their exposure to Latin American markets after 1998 and increased it again in 2003.

Remarkable in Figure 2 c) is the strong exposure to the MSCI EM EMEA which hedge funds built up after 2001. After March 2004, however, we see a strong drop in the exposure of hedge funds. In April 2004 the respective index had a negative return of 8.70%. Unfortunately, our data does not allow us to investigate whether the reduced exposure was due to the negative returns or whether the hedge fund managers reduced their exposure before the losses occurred. With respect to the MSCI EM Asia and the MSCI EM EMEA, hedge funds have an exposure which changes more over time than does the exposure of mutual funds. This indicates that hedge funds are more active with respect to geographic asset allocation, perhaps in an effort to time the market.

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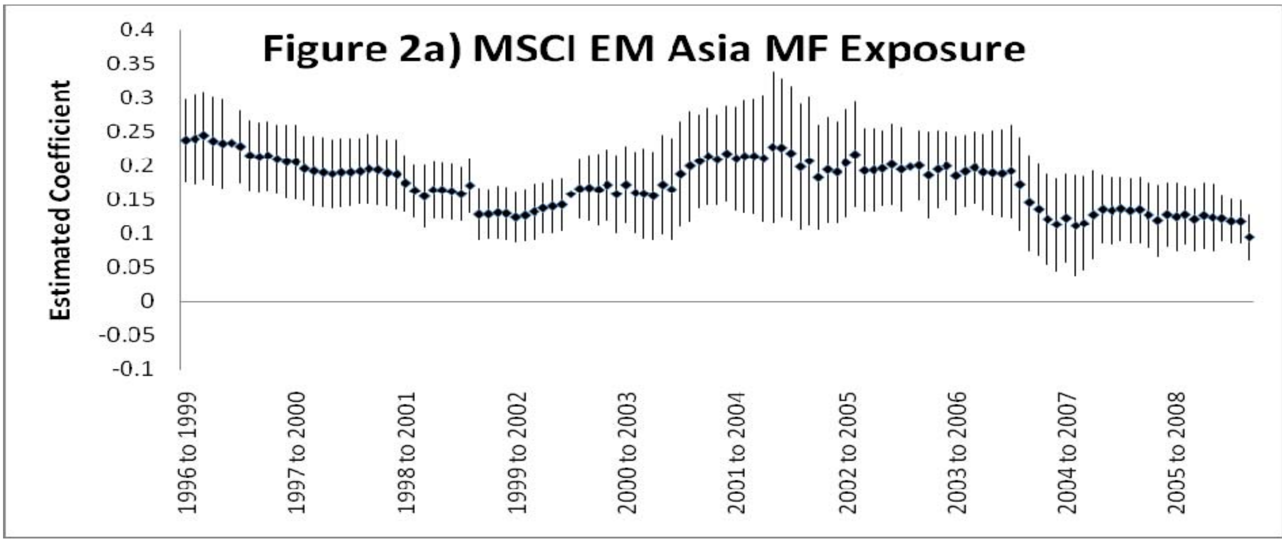
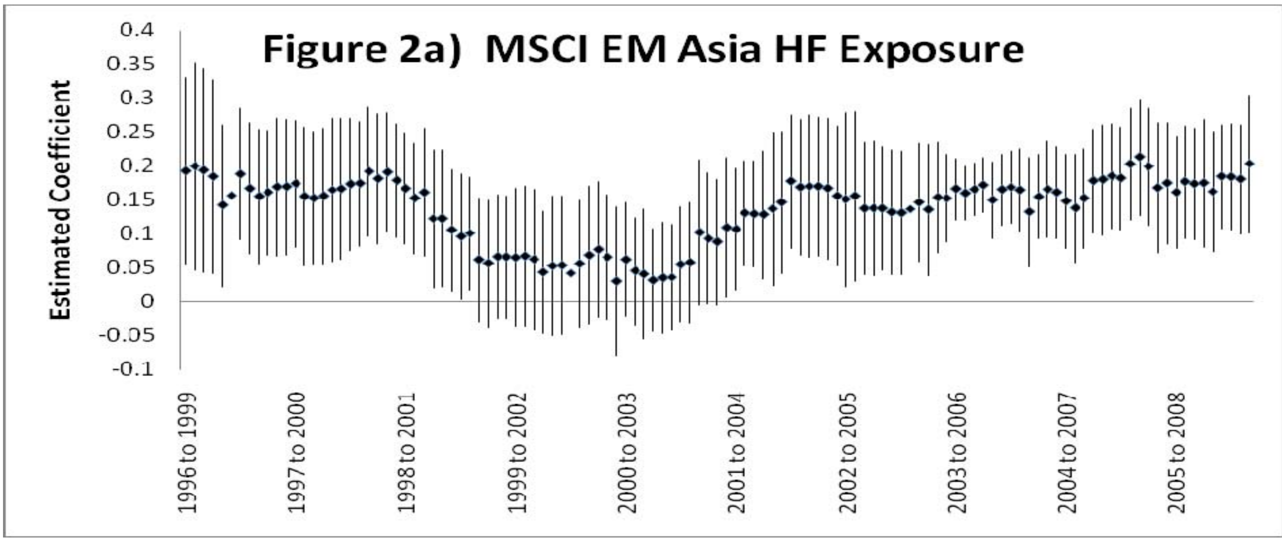
[25] Results from a rolling regression for all other factors are available from the authors upon request.





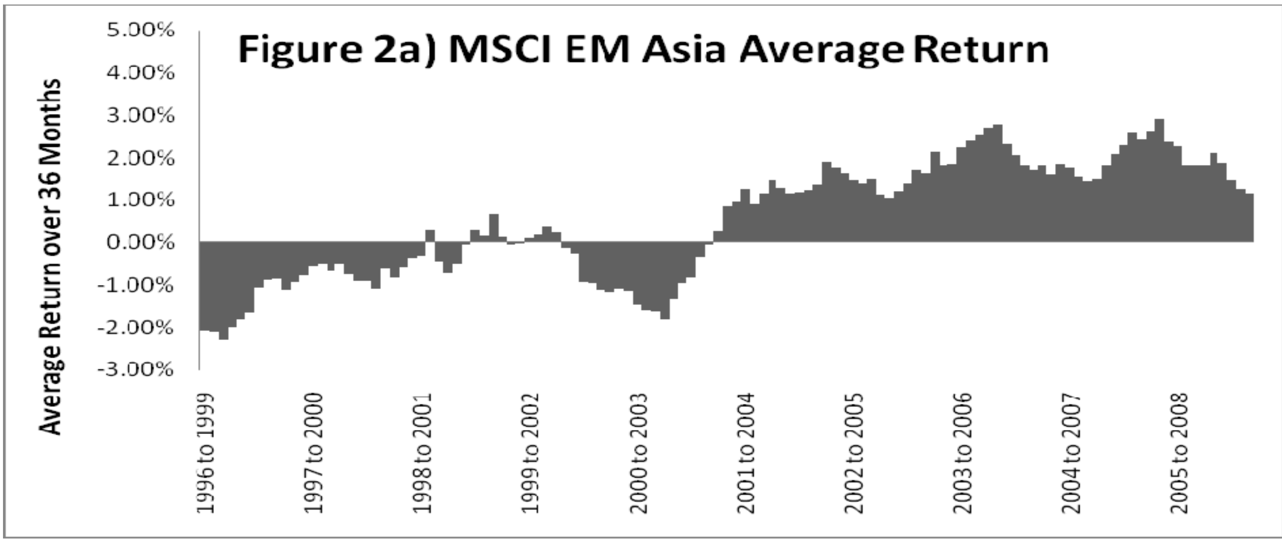
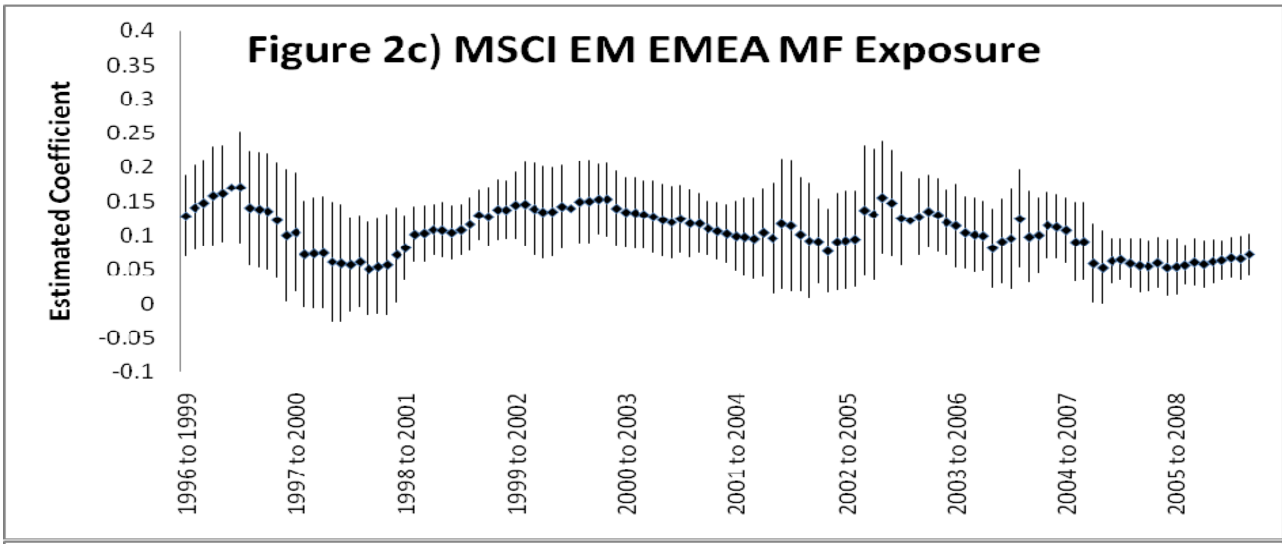
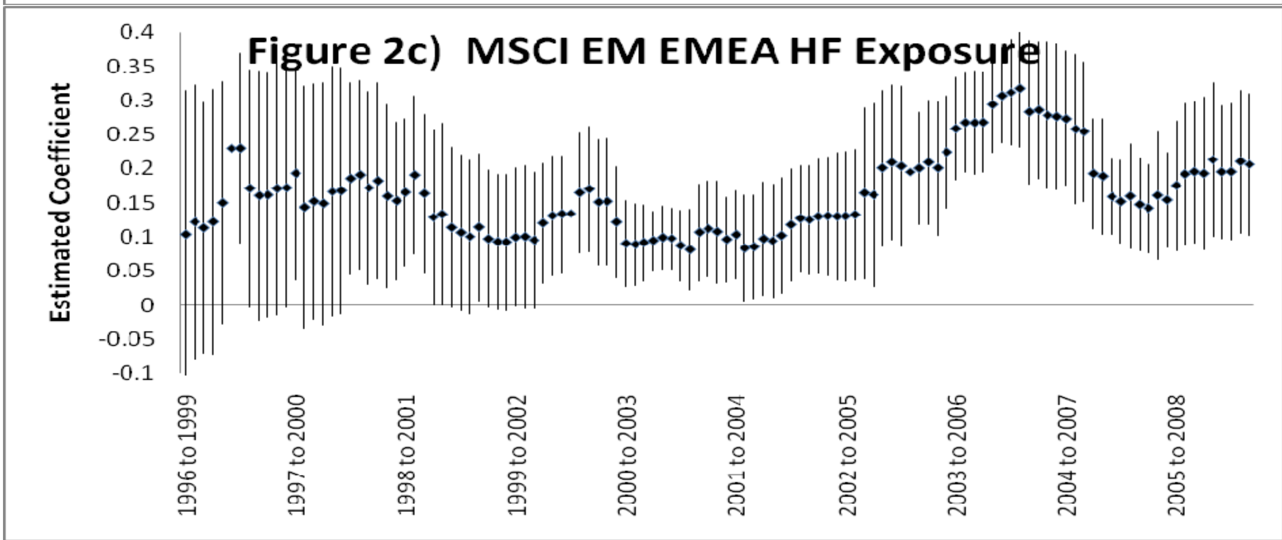


Figure 2: Rolling regression of factor exposure for mutual funds (top), hedge fur

Figure 2 a) and the MSCI EM Latin America (right, Figure 2b)





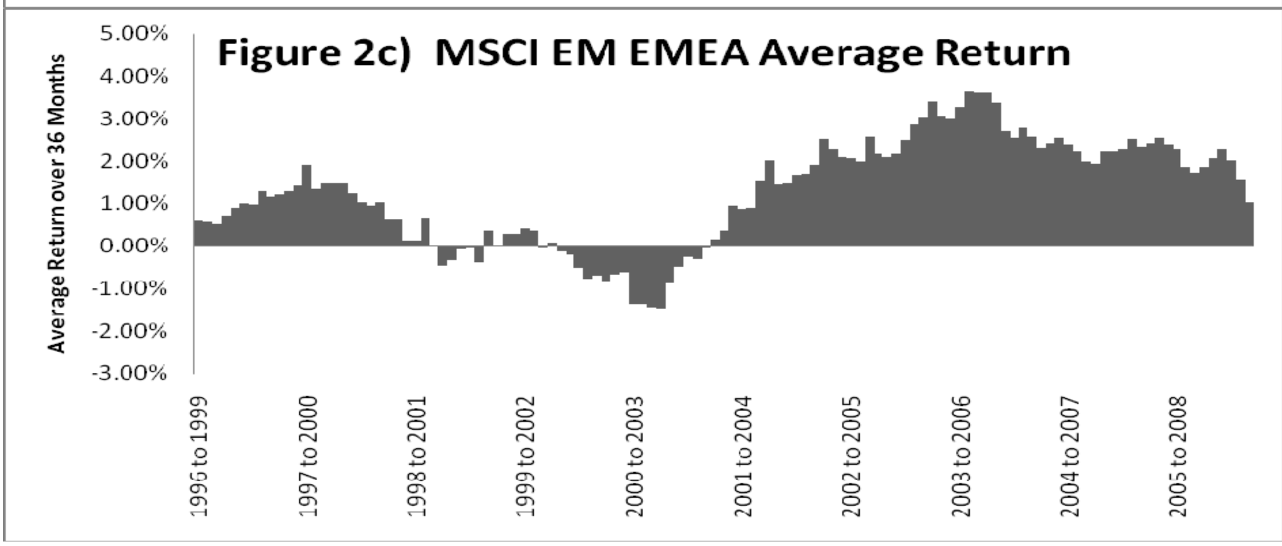


Figure 2: Rolling regression of factor exposure for mutual funds (top), hedge fu
ure 2 c) and the sum of the estimated coefficients from a rolling regression over
of the MSCI EM and the JP Morgan EMBI Bond indices (right, 2 d)

Regarding Figure 2 d) the exposure of hedge funds to equities seems to go down after the period 1998 to 2001 and stays on a lower level before it increases again two years later. In the period from 2000 to 2003 where emerging market equities had on average negative returns, hedge funds reduced their exposure to equities, an observation which we cannot confirm for mutual funds. In general the mutual funds were holding a nearly constant exposure to equities which was only slightly reduced over time. A possible explanation might be that they are ether obliged by investment policies to do so or that they do not try to time the markets by asset allocation. The exposure to bonds should be interpreted with more caution because the confidence intervals for the bond exposure are larger than those for equities. The hedge funds seem to have a higher exposure to bonds than mutual funds around the period 2000 to 2003 what is again support for the thesis that hedge funds, opposed to mutual funds, were able to time the asset allocation between bonds and equities. While the hedge funds always have a positive exposure to the lagged bond returns, this is not the case for the mutual funds. An explanation for the hedge funds could be illiquid positions which are infrequently priced or not adequately market priced. Another reason might be return smoothing.

Another question that has recently been the subject of much research is whether the hedge fund alpha has declined in the last several years. Naik et al. (2007) report that hedge funds generated significant alphas in the decade between 1995 and 2004, but that the level of alpha declined substantially over this period. Their two explanations for this effect are (1) large capital inflows that are followed by negative movements in alpha and (2) that hedge fund fees have increased over this time. Fung et al. (2008) analyze funds of funds and also emphasize that large capital inflows attenuate the ability to produce alpha in the future. According to their study, the average fund of fund delivered a significant positive alpha only between October 1998 and March 2000. To see what light our work can shed on this topic, Figure 3 a) presents the adjusted R^2 of a rolling regression and Figure 3 b) the estimated alpha over our sample period.

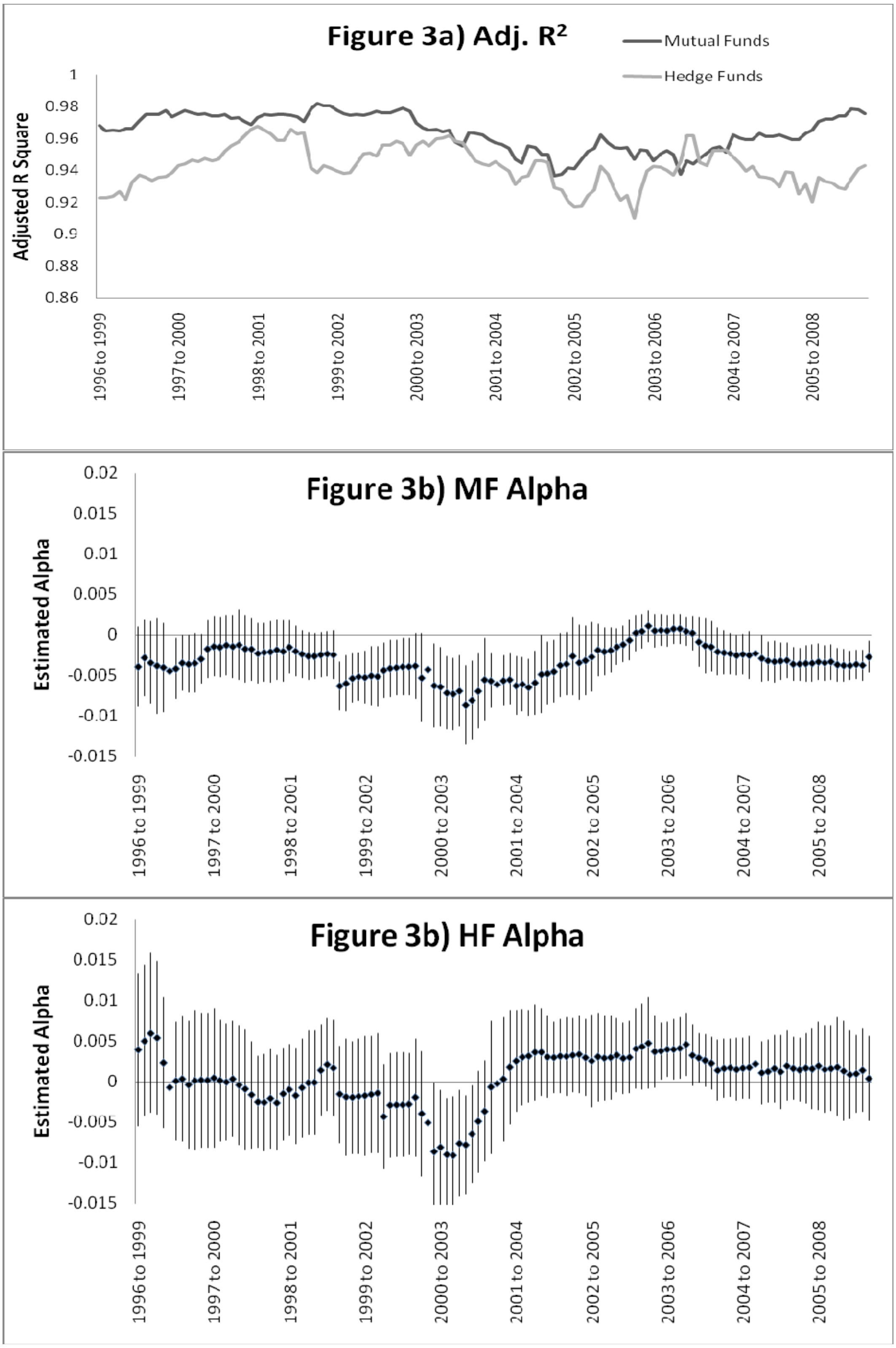


Figure 3: a) Adjusted R^2 of a rolling regression for mutual funds and hedge funds and b) Alpha of a rolling regression for mutual funds (top) and hedge funds (bottom) with 90% confidence interval

Our empirical results provide no support either for Fung et al. (2008) or for Naik et al. (2007). First, we do not find that emerging market hedge funds had excellent performance between October 1998 and March 2000; instead, this was a period of declining alpha values. Second, we cannot confirm that hedge funds alpha has decreased over the investigation period as the best alpha values are found in the second half of this timeframe. These empirical findings are in line with Strömqvist (2007), however, who also cannot identify a decrease in performance in recent years. Only during the last few years (mid-2003 to 2008, a period not fully considered in Strömqvist, 2007), does alpha decrease slightly, especially for the mutual funds. When comparing hedge funds and mutual funds, we find the latter underperform during the stock market plunge, only beginning to recover starting in 2003. As to explanatory power (Adjusted R^2 in Figure 3 a), we do not see much variation for either type of fund.

4.5. Performance measurement results for different market environments

The results so far suggest that hedge funds and mutual funds have different abilities in generating returns during bear markets. To analyze this hypothesis in more detail, we consider fund performance in different market environments. We therefore subdivide the returns of the MSCI emerging market index (we choose this index as a reference because of its high correlation with mutual funds and hedge funds) into four different market environments, ranging from severe declines to sharp rallies, by sorting the monthly returns into four quartiles (see Fung and Hsieh, 1997). Market environment 1 contains the worst 36 months of the MSCI index; market environment 4 the best 36 months. The average returns are then calculated for the MSCI index as well as for mutual fund and hedge fund returns in these months. The results are presented in Figure 4.

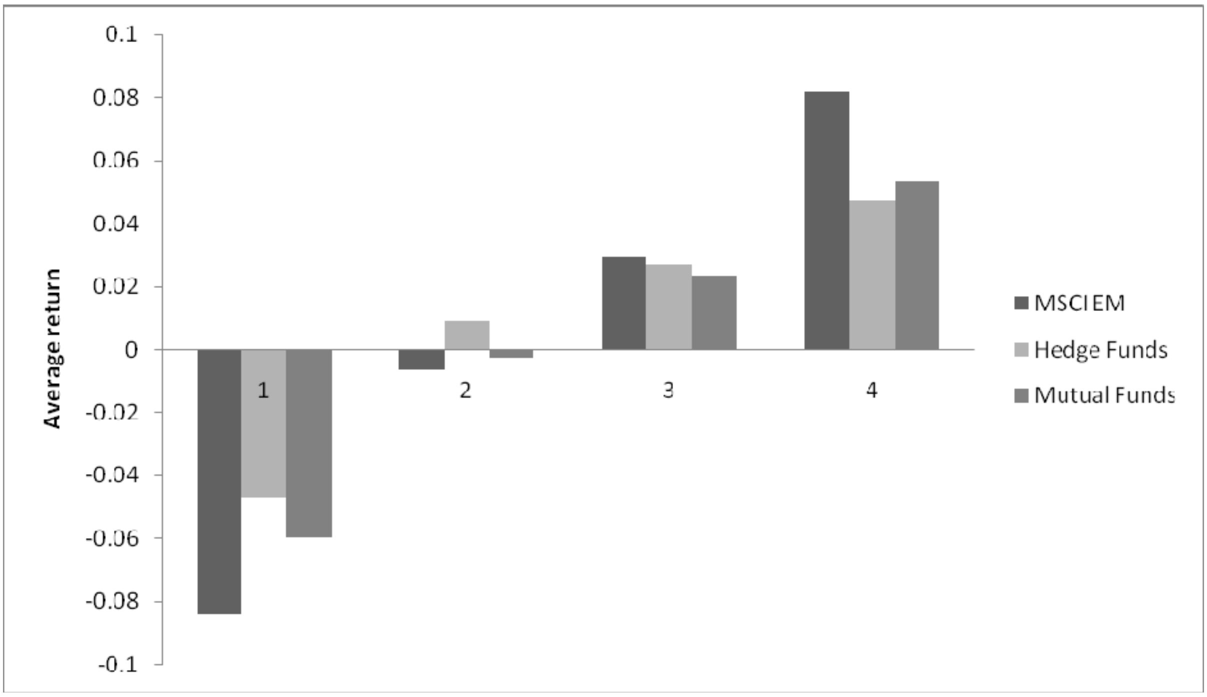


Figure 4: Returns in different market environments (1: worst months for MSCI EM, 4: best months for MSCI EM)

Not surprisingly, given the correlation of 0.96, the returns of mutual funds and the market index are very comparable. Overall, the beta of the mutual fund portfolio with regard to the MSCI EM is lower than 1, as the mutual fund portfolio tends to be less extreme, i.e., in the worst months (market environment 1) mutual funds are slightly better than the index and in the best months (market environment 4), mutual funds underperform the market. Hedge fund returns are almost identical to the mutual fund returns in good market environments (market environments 3, 4). Interestingly, however, in bad market environments (market environments 1, 2) hedge funds outperform both the market as well as their mutual fund competitors. It thus appears that mutual funds have a relative constant exposure with regard to different market environments, whereas hedge funds might be able to profit from non-directional strategies, providing, at least to some extent, downside protection in an unfavorable market environment (market environment 1, 2).

5. Conclusion

The contribution of this paper is twofold: In a first step, we develop an asset class factor model to describe the performance of hedge funds and mutual funds investing in emerging markets. Our results indicate that the market-related factors chosen for our model are much better at explaining the variation in emerging market returns than are non emerging market specific factor models presented in the literature and that they are slightly better than the emerging market specific model of Abugri and Dutta (2009). Our model explains a large proportion of the variation in both mutual fund and hedge fund returns.

The second contribution of this paper is to employ various factor models to compare returns of hedge funds and mutual funds active in emerging markets. We find that hedge funds provide both higher returns and alphas than do traditional mutual funds. These findings are in line with other recent literature (Abel and Fletcher, 2004; Strömqvist, 2007). In general, some hedge funds tend to outperform the benchmarks, but most traditional mutual funds do not. One possible reason could be more active management of hedge funds than of mutual funds. We find support for this hypothesis from the tests for structural breaks, the factor exposure, and from the analysis of the performance in different market environments. Regarding structural breaks, we only find significant breakpoints for hedge funds but not for mutual funds. This indicates that hedge funds are adjusting their risk taking while mutual funds are not. The factor exposure of hedge funds, which we reveal using a rolling regression, shows that hedge funds have a more volatile exposure, supporting the idea of a more active management. The analysis of different market environments shows that hedge funds provide to some extent downside protection in contrast to mutual funds that have a rather constant exposure to market movements.

In conclusion, it seems that emerging market hedge funds are more active in shifting their asset allocation, probably since they are less restricted by their investors in investment style and policy. Furthermore, it is plausible that hedge fund style shifts have been especially pronounced in the most recent period (post 2006) since more alternative instruments, such as options and futures, are becoming available in emerging markets and hedge funds are not restricted in using them. It might thus also be that emerging market hedge funds now behave more like other hedge funds (see Abugri and Dutta, 2009), but we believe that additional research with more recent data is necessary to confirm this assertion, since the last, most recent subperiod analyzed is relatively short.

However, investors need to be aware that (aside from the differences in their flexibility regarding asset allocation) there are numerous reasons which might be responsible for the performance difference between mutual funds and hedge funds, including the use of leverage, lock-up periods, and incentive fees for hedge fund managers. Lock-up periods are also a good example to emphasize the higher degree of freedom hedge fund managers enjoy in making investment decisions. For example, hedge funds might invest in illiquid positions and capture liquidity risk premiums, actions not allowed to traditional mutual funds (see Ding et al., 2009, for an analysis of liquidity in the hedge fund context). In case of illiquid investments, investors need to be aware that hedge fund managers might smooth their returns (see Getmansky et al., 2004), which might bias performance measurement results.[26]

Kouwenberg and Ziemba (2007) illustrate that incentive fees and manager's own investment in the fund substantially affect the investment strategy of hedge fund managers. Both these elements are not widespread with traditional mutual funds. Furthermore, hedge funds are not subject to much regulation. Hedge funds in the United States are usually set up as limited partnerships, a legal form only lightly regulated, and hedge funds outside the United States are usually domiciled offshore, a practice that has both regulatory and tax advantages. All

[26] Note that our study design accounts for other biases in hedge fund returns such as survivorship and backfilling bias; these other biases thus do not distort the performance measurement results. Overall, we thus believe that data biases can only partly explain the observed performance differences between hedge funds and mutual funds.

these advantages make hedge funds the more flexible investment scheme, both as to investment strategy and markets in which to invest. During the financial crisis hedge funds have been severely criticized and it is not clear whether future regulation in the financial services sector might diminish these regulatory advantages of hedge funds.[27] Overall, it thus seems that a combination of technical problems (e.g., return smoothing) and economic advantages (e.g., higher flexibility and lower regulation) might account for the observed performance differences between hedge funds and mutual funds.

The factor model developed in this paper can be put to a number of different uses. First, investors can use the model to identify well-performing funds in which to invest. Although past performance is not necessarily an indicator of future returns, investors heavily rely on past performance when making investment decisions (see Capon et al., 1996). Second, the model can be a tool for determining manager compensation as the model can detect whether a fund's performance is mainly attributable to passive investment style or something more proactive. The model makes it possible to reward managers for only those returns superior to a specific benchmark, and thus attributable to the fund manager's skill. Third, the model can be used for risk management as revealing the underlying assets will help identify the true risk of a fund. This might be especially relevant in identifying a drift in management style; catching any such changes early will help keep a portfolio both safe and profitable.

[27] An interesting application of our model would be to measure performance in the recent times of crisis, e.g. with regard to structural breaks or with regard to shifts in asset allocation. However, due to the substantial data reporting lags such an investigation is not feasible yet. For example, the CISDM database considered in this paper is released with a six to twelve month lag. An analysis of hedge funds in times of financial crisis and its biggest hits (that occurred so far in the second half of 2008) can thus not be undertaken before 2010 or 2011. The analysis of the Asian crisis presented in this paper, however, illustrates the substantial impact of these big events on both hedge fund and mutual fund performance.

	Panel A: Measurement Value					Panel B: Ranking					Panel C: Test	
	Sharpe Ratio	Modified Sharpe Ratio (Israel-sen)	Modified Sharpe Ratio (Grego-riou and Guyie)	Sortino Ratio	Calmar Ratio	Sharpe Ratio	Modified Sharpe Ratio (Israel-sen)	Modified Sharpe Ratio (Grego-riou and Guyie)	Sortino Ratio	Calmar Ratio	Jobson and Korkie (1981)Test	Signi-fic-ance
Hedge Funds	0.20	0.20	0.08	0.29	0.03	2	2	1	2	2	/	
Mutual Funds	0.09	0.09	0.04	0.12	0.01	15	15	17	16	16	2.86	***
Market Proxy	0.10	0.10	0.05	0.15	0.02	10	10	11	10	8	1.31	
SMB*	0.06	0.06	0.03	0.10	0.01	20	20	21	19	22	1.34	
HML*	0.12	0.12	0.06	0.18	0.02	9	9	7	9	6	0.57	
Momentum*	0.16	0.16	0.07	0.23	0.02	6	6	4	5	9	0.36	
MSCI North Am.	0.10	0.10	0.05	0.14	0.02	12	12	12	12	10	1.27	
MSCI non-US	0.08	0.08	0.04	0.11	0.02	16	16	19	18	15	1.65	*
IFC Emerg. Markets	0.10	0.10	0.05	0.14	0.02	11	11	14	11	13	2.03	**
JPM US Gov. Bonds	0.15	0.15	0.07	0.23	0.03	7	7	3	6	3	0.38	
JPM Non-US	0.06	0.06	0.04	0.10	0.01	19	19	18	20	18	1.03	
Eurodollar Deposit	-0.04	0.00	-0.02	-0.06	-0.01	26	27	26	26	26	1.99	**
Gold	0.07	0.07	0.04	0.11	0.01	18	18	15	17	19	1.12	
US Dollar*	0.02	0.02	0.01	0.03	0.00	25	25	25	25	24	1.92	*
S&P 500	0.10	0.10	0.05	0.14	0.02	13	13	13	13	12	1.28	
Size*	0.03	0.03	0.01	0.04	0.00	24	24	24	23	25	1.58	
Bond*	-0.05	0.00	-0.03	-0.08	-0.01	27	26	27	27	27	2.24	**
Credit*	0.07	0.07	0.05	0.12	0.01	17	17	10	15	17	0.87	
TFBond*	-0.13	0.00	-0.10	-0.19	-0.02	28	28	28	28	28	2.26	**
TFCur*	0.04	0.04	0.03	0.07	0.01	22	22	22	22	20	1.21	
TFCom*	0.04	0.04	0.04	0.08	0.01	21	21	20	21	21	1.19	
MSCI EM Total	0.09	0.09	0.04	0.13	0.02	14	14	16	14	14	2.26	**
MSCI EM Asia	0.03	0.03	0.01	0.04	0.01	23	23	23	24	23	2.52	***
MSCI EM EMEA	0.15	0.15	0.07	0.22	0.02	8	8	5	8	5	0.90	
MSCI EM Latin Am.	0.17	0.17	0.08	0.25	0.03	4	4	2	3	1	0.59	
JPM EM Asia	0.23	0.23	0.06	0.32	0.02	1	1	6	1	4	-0.22	
JPM EM Europe	0.18	0.18	0.05	0.23	0.02	3	3	9	4	11	0.28	
JPM EM Latin Am.	0.16	0.16	0.06	0.22	0.02	5	5	8	7	7	0.56	

Note: The Jobson and Korkie (1981) test in Panel C measures the difference between the Sharpe ratio of hedge funds and the alternative indices. * (**, ***) indicates significance at 10% (5%, 1%) level. For example, with a test statistic of 2.86 the performance difference between hedge funds and mutual funds is highly significant at 1% level.

Appendix: Performance of hedge funds, mutual funds, and passive investment strategies

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