Hedge Funds and International Capital Flows

Maria Strömqvist

STOCKHOLM SCHOOL OF ECONOMICS

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To my family

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Introduction and Summary

This thesis consists of four chapters that investigate the performance and capital flows of hedge funds. In this section an introduction to hedge funds is given followed by a summary of the chapters.

There is no exact definition of a "hedge fund". Generally speaking, a hedge fund is any privately-offered, absolute-return fund for financially sophisticated investors. Although many hedge funds attempt to offset potential losses by hedging, the term "hedge fund" is loosely defined and hence, not all such funds use hedging techniques. Instead, hedge funds employ many different types of strategies using non-traditional portfolio management techniques.

One way of understanding hedge funds is in relation to something more familiar, like mutual funds. Both hedge funds and mutual funds are investment vehicles that aim at providing their investors with returns on their investments. However, the investment strategies employed by the two are different. Mutual funds mainly use buy-and-hold strategies, where they only take long positions in liquid assets. Hedge funds implement more dynamic trading strategies, involving both long and short positions in sometimes illiquid assets. Moreover, hedge funds typically leverage their bets while the use of leverage is often limited for mutual funds. Hedge funds also have greater freedom in the types of securities in which they invest, including financial derivatives.

Another distinction is how the performance is evaluated. Mutual funds usually benchmark their performance against an index, i.e. they have relative return targets. Hedge funds, on the other hand, have absolute return targets that are independent of market return. This has implications for how the managers are rewarded. With their absolute return targets, hedge funds often specify a hurdle rate. That is, the fund must deliver an established minimum return on investment before any performance fee is paid to the managers. Moreover, unlike mutual funds, hedge funds are allowed to have asymmetric fees. The asymmetry means that the fee will increase with good performance but does not decrease with bad performance, similar to an option. On average, hedge fund managers receive two percent annual management fee and 20 percent of the profits. Hedge funds can also have a "high-water mark". This means that their managers will only be rewarded if the value of the investment in this period exceeds the greatest level in the past, the high-water mark.

Hedge funds are generally structured as partnerships, with the general partners being the portfolio managers making the investment decisions, and the limited partners being the investors. As general partners, the fund managers typically invest a significant portion of their personal wealth in the fund to ensure the alignment of economic interests between managers and investors. Moreover, many hedge funds have a high minimal capital requirement, typically in the range of $250,000 to $1 million.

Finally, investors in hedge funds are often financially sophisticated, unlike the retail investors in mutual funds. Thus, hedge funds have largely remained unregulated. U.S. hedge funds do not have to (but can voluntarily) register with the Securities and Exchange Commission.[1] Hence, hedge fund data are self-reported by the funds.

Generally speaking, this thesis analyzes the performance and capital flows of hedge funds over the period 1994 to 2004. The hedge fund dataset used in all chapters is collected from four large hedge fund databases[2], giving a representative sample of the hedge fund industry. In total, 7600 hedge funds are used in the analyses.

The first two chapters of the thesis focus on hedge funds that have a pure emerging market strategy. Hedge funds should be well equipped to take advantage of opportunities in emerging markets due to their flexibility in investment strategy and lockup periods. However, the results in the first chapter show that, at the strategy level, emerging market hedge funds have only generated risk-adjusted returns in the most recent years of the sample period. The poor return can partly be explained by the finding that good performance is not rewarded with capital inflows. This reduces incentives for managers to exert effort and may even deter skillful managers from entering the strategy. Consistent with these results, investors have reallocated their money to other hedge fund strategies. Although emerging market hedge funds have performed poorly in the past, an important finding is the upward trend over time in performance. Given that other hedge fund strategies have a declining trend in alpha during the same period, the emerging market strategy may be where future alpha can be found.

[1] In Sweden, hedge funds are registered as "Specialfonder" and have to report monthly returns, six-month standard deviations and their five largest holdings.
[2] The databases are HFR, TASS, CISDM and MSCI.

The second chapter extends the results in Chapter 1. Given the poor performance on average, the main objective of the second chapter is to investigate how an investor in emerging market hedge funds can achieve higher returns. First, the findings show that emerging market funds that specialize in a specific geographic region have a higher risk-adjusted return than funds that have a global strategy. This can be explained by an informational advantage as well as a positive effect from specialization. Second, funds that enter the sample during a down-market and have positive risk-adjusted return in that period are more likely to perform well consistently than other funds. This can help investors separate between true alpha generating funds and more opportunistic funds. And finally, the results display that, despite the poor performance and the high performance fees, an investor is still better off investing in hedge funds than mutual funds in emerging markets.

The third chapter investigates if there are capacity constraints in hedge fund strategies. The idea is that the alpha opportunities in the markets are limited. Thus, the more capital coming in to hedge funds, the higher competition for the investment opportunities. The findings reveal that four out of eight strategies show evidence of capacity constraints. That is, high past capital flows have a negative effect on current risk-adjusted returns. This is mainly true for strategies that rely on liquidity in their underlying market, such as Relative Value or Fixed Income. Other strategies, for example Security Selection, do not exhibit capacity constraints.

The last chapter investigates the out-of-sample performance of five allocation models relative to an equally weighted portfolio, when optimizing over hedge fund strategies. The findings show that for hedge fund investors the naive allocation model (1/N) with equal weights in each asset is not an efficient allocation. The risk-adjusted performance can be improved by using an optimal sample-based allocation model. Moreover, significant improvement in out-of-sample alpha can be made if the investor optimizes over non-systematic returns instead of total returns, which is an important results for investors seeking alpha.

Chapter 1

Should You Invest in Emerging Market Hedge Funds?

Maria Strömqvist*

Abstract

Hedge funds should be well equipped to take advantage of opportunities in emerging markets due to their flexibility in investment strategy and lockup periods. However, the findings in this paper show that, at the strategy level, emerging market hedge funds have only been able to generate risk-adjusted returns in the most recent period when analyzing data between 1994 and 2004. Also, the strategy in question does not present the investor with any benefits that would be valuable in a hedge fund portfolio. There is weak evidence of persistence in risk-adjusted returns at the fund level. However, good performance is not rewarded with capital inflows. This reduces incentives for managers to exert effort and may even deter skillful managers from entering the strategy. Consistent with these results, investors have reallocated their money to other hedge fund strategies. Although emerging market hedge funds have performed poorly in the past, an important finding is the upward trend over time in performance. Given that other hedge fund strategies have a declining trend in alpha (Fung et al. 2007), perhaps emerging market funds are where future alphas can be found.

Keywords: *Hedge funds; alpha; factor models; emerging markets; performance persistence; flows*

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1 Introduction

This paper investigates the combination of emerging markets and hedge funds from the investors' point of view. Hedge funds have several advantages over traditional investment vehicles when investing in these markets. For example, they have the opportunity to both take long and short positions, thus being able to better take advantage of the volatility in emerging markets. Other advantages are the possibilities to use leverage and derivatives. Hedge funds also have the opportunity to lock in their investors for a period of time, and thus better handle illiquid assets, not having to worry about withdrawals from the fund. Hence, hedge funds should be well equipped to deal with the characteristics of emerging markets, and thus provide value due to active management. The question of interest is – have they succeeded in doing so?

The performance and capital flows of emerging market hedge funds are analyzed both at the strategy- and fund level using data from 1994 to 2004. The first half of the paper analyzes the performance at the strategy level and its implications for capital flows to emerging market hedge funds. The research questions are the following: First, how have emerging market hedge funds performed in absolute terms and relative to other hedge fund strategies? Second, does the strategy add value to a portfolio of assets? Third, to what extent have investors allocated money to emerging market hedge funds during the period studied? And fourth, which factors determine the capital flows into this strategy?

The second half of the paper investigates the performance at the fund level, focusing on the generation of risk-adjusted return (alpha). The following questions are asked: Do funds only generate alpha by luck or is there persistence over time? What factors affect the level of alpha? And finally, can investors differentiate between good and bad funds (in terms of risk-adjusted returns)?

There are two main (expected) benefits that motivate investments in any assets. The first is if the asset provides a superior return relative to alternative investments, and the second is if it offers diversification benefits in a portfolio of assets. The analysis at the strategy level reveals that the emerging market strategy has only been able to generate risk-adjusted returns in the most recent period. Moreover, the strategy in question does not present the investor with any diversification benefits that would be valuable in a hedge fund portfolio. What is positive, however, is that emerging market funds do not display the same pattern as other hedge funds with declining risk-adjusted returns (see Fung, Hsieh, Naik and Ramadorai (2007)).

Despite the underperformance of this strategy, it has received an almost exponential inflow of capital during recent years. The level of capital flows depends positively on past own-strategy return and negatively on the return of other hedge fund strategies. Emerging market funds have also experienced a higher capital inflow in periods when the diversification benefits of investing in emerging markets are higher. However, the strategy's share of the hedge fund industry's total capital flows has decreased significantly during the same period. This indicates that investors have reallocated money to other hedge fund strategies.

Even though emerging market hedge funds have performed poorly at the strategy level, there is some evidence of weak persistence in risk-adjusted returns at the fund level. When sorting funds on past risk-adjusted return, funds with alpha in the previous period outperform other funds. These "Alpha funds" are also valuable in a portfolio of assets. However, the persistence in performance is strongest in periods when the return on the stock market is high, especially in the latter part of the sample period. The results also show that good performance reduces the probability of the fund being liquidated in the future. Although there are a few funds that perform consistently well, they do not receive more capital inflows than other funds.

The fund level analysis provides several explanations for underperformance at the strategy level. First, the fact that emerging market funds tend to do better in periods when the return on the stock market is high indicates that they are constrained by limited liquidity. Second, for emerging market hedge funds, good performance (in terms of risk-adjusted returns) is not rewarded with capital inflows. This reduces the incentives for managers to exert effort, take risky bets and may even deter skillful managers from entering the strategy.

This paper contributes to existing literature by being the first paper to thoroughly investigate the performance and capital flows of emerging market hedge funds. Not only does this paper provide a comprehensive analysis of the generation of risk-adjusted returns over the sample period, but also of the behavior of investors. The results have important implications. The fact that hedge funds, that are considered to be the ultimate arbitrageurs, have struggled to generate risk-adjusted returns in emerging markets is of concern. The analysis shows the importance of not only picking the right fund to invest in but also the importance of timing the market. Although the emerging market strategy has performed poorly in the past, an important finding is the upward trend in performance over time. Given that other hedge fund strategies have a declining trend in alpha[1], emerging market funds might be where future alphas can be found.

1.1 Related Literature

Little research has been done on the combination of emerging markets and hedge funds, partly due to lack of data. Only two previous papers deal with this issue, Eichengreen, Mathieson, Chadha, Jansen, Kodres and Sharma (1998) and Fung and Hsieh (2000*a*). The objective in both studies is to determine to which extent hedge funds have exerted a market impact. After the devaluation of the Sterling in 1992 and the Asian crisis in 1997, it was suggested that hedge funds earn superior returns at the cost of financial stability. However, both Eichengreen et al. (1998) and Fung and Hsieh (2000*a*) find little evidence of hedge funds exerting market impact and no evidence of hedge funds using positive feedback trading strategies.

According to Eichengreen et al. (1998), hedge fund managers are attracted to emerging markets because of the opportunity of identifying fundamentals that are far out of line. Such events would cause large changes in asset prices (and hence associated profits) when they finally occur. In these situations, the risk of large capital losses would be very low.[2] Moreover, in countries with a weak currency, foreign investors get more value for their

[1] See Fung et al. (2007) and the article "Hedge fund sheep in wolves' clothing" in *Financial Times* on July 2, 2007.

[2] An example is the Argentine crisis in 2001. The government of Argentina defaulted on its debt, and the Argentine peso, which used to be pegged at par with the U.S. dollar, reached lows of 3.9 per U.S. dollar (Daseking, Ghosh, Lane and Thomas (2004)). Hence, during the Argentine crisis, there was a large probability that the exchange rate would be devalued but almost no probability that it would be revalued.

dollars. Cheap funding allows hedge funds to take and hold a position in emerging markets even when they are uncertain about the timing.

Although emerging markets present investors with good investment opportunities, there are also less attractive features. Limited liquidity and the limited size of accepted deals can constrain the ability of hedge funds to build up positions. On the other hand, once entering large positions, they can be difficult to off-load and thus, the profits may not be realized in time. High transaction costs also pose a problem to investors. In a survey by Chuhan (1992), poor liquidity is mentioned as one of the main reasons that prevent foreign institutional investors from investing in emerging markets.

Hedge funds are also known for not wanting to disclose more information than necessary regarding their trades. Anonymity is particularly difficult to maintain in smaller, less liquid markets. In Eichengreen et al. (1998), it is stated that hedge fund managers are wary of being identified as being on the other side of government or central bank transactions out of fear of economic retaliation or political retribution.

The returns of hedge funds in general have been thoroughly investigated in the literature. The focus has been on the claim of market neutrality and finding a suitable factor model for evaluating hedge fund alpha. Fung and Hsieh (1997*a*), Fung and Hsieh (2001), Mitchell and Pulvino (2001), and Agarwal and Naik (2004) show that hedge funds' exposures to risk factors have option-like features. Building on that, Fung and Hsieh (2004*b*) use asset-based style factors to create hedge fund benchmarks that capture the common risk factors in hedge funds. They identify seven risk factors that can jointly explain between 60 and 80 percent of the return movements in hedge fund portfolios.

Despite not being market neutral, many papers still claim that hedge fund groups display positive unexplained returns, providing evidence of manager skill (see, for example, Liang (1999)). Fung and Hsieh (2004*a*) show empirically that Equity Long/Short hedge funds have significant alpha to both conventional as well as alternative risk factors. Kosowski, Naik and Teo (2007) examine hedge fund returns using a bootstrap methodology, showing that the performance of the top hedge funds cannot be attributed to chance alone. Moreover, both Kosowski et al. (2007) and Fung et al.

(2007) find evidence of persistence in alpha when sorting funds based on their alpha t-statistics.

Finally, an important issue in the emerging market setting is investments in illiquid assets. Getmansky (2004) shows that hedge funds in illiquid categories are subject to high market impact and have limited investment opportunities. Aragon (2007) finds a positive, concave relation between the returns and the share restrictions of hedge funds. He concludes that previously documented positive alphas can be interpreted as compensation for holding illiquid fund shares.

The rest of the paper is organized as follows. The next section presents the data and summary statistics and section three the methodologies used. In section four, performance and capital flows at the strategy level are investigated. The next section analyzes performance at the fund level. Finally, section six discusses the results and the last section concludes.

2 Data and Summary Statistics

2.1 Hedge Fund Data

In this paper, hedge fund data from four large databases are used; HFR, TASS, CISDM, and MSCI, giving a representative sample of the hedge fund industry. Using data from all four databases, after eliminating duplicates, will minimize any selection bias. The monthly data begin in January 1994 and end in December 2004. The dataset includes dead funds, which minimizes survivorship bias.[3] To be included in the dataset, a fund is required to have at least 12 months of data. Only funds that report assets under management (AUM) are included in the dataset. All funds that have an inflow greater than 500 percent or an outflow greater than 100 percent of the AUM of the previous month are eliminated. Thus, the total dataset consists of about 7600 hedge funds, 418 of which are classified as emerging market hedge funds. Table I shows that the average life of emerging market hedge funds is 4.4 years and the average size is about 76 million

[3]The survivorship bias in hedge fund data has previously been estimated to between 2-3 percent per year. See, for example, Fung and Hsieh (2000*b*), Brown, Goetzmann and Ibbotson (1999), Liang (2000) and Edwards and Caglayan (2001).

dollars over the sample period. This can be compared to the numbers for non-emerging market hedge funds for which the average life is 4.5 years and the average amount of assets under management is 100 million dollars.

2.1.1 Return Data

Value-weighted excess return indices are computed at a strategy level and are constructed as

$$r_{st}^{VW} = \sum_{i=1}^{N} w_{it}(r_{it} - r_{ft}) \tag{1}$$

where

$$w_{it} = AUM_{it-1} / \left(\sum_{i=1}^{N} AUM_{it-1} \right) \tag{2}$$

are AUM weights reconstructed each month, r_{it} is the net-of-fee return on fund i in month t, r_{st} is the return in month t for strategy s and r_{ft} is the return of the three-month U.S. Treasury bill in month t.

The average monthly excess return for emerging market hedge funds during 1994 to 2004 is 0.48 percent (see Table I).[4] The median, however, is more than twice as high as the mean, indicating that there are some high negative returns in the sample. The minimum is as much as –23 percent in the month of August 1998. This was a period of turbulence with the Asian and Russian crises as well as the crisis of Long-Term Capital Management (LTCM). The maximum monthly return is 15 percent in December 1999, during the technology boom. The large spread of returns over the sample period is shown in the standard deviation of almost five percent per month. Non-emerging market hedge funds have a slightly higher average return and lower volatility, as can be seen in Table I.

2.1.2 Flows

The dollar flows for each fund are calculated as follows:

[4]Regarding potential backfill bias, excluding the first twelve months of data for each fund will only reduce the average monthly excess return from 0.48 percent to 0.46 percent.

$$F_{it} = AUM_{it} - (1 + r_{it})AUM_{it-1}. \tag{3}$$

The AUMs are assets under management at the end of the month, and it is assumed that flows come in at the end of the month, after the accrual of returns. Flows at the strategy level are calculated by aggregating individual fund flows and scaling the dollar flows by strategy-aggregated end-of-previous-month AUM:

$$f_{st} = \left(\sum_{i=1}^{s} F_{it}\right) / \left(\sum_{i=1}^{s} AUM_{it-1}\right). \tag{4}$$

Table I displays summary statistics for the strategy flow as a percentage of the strategy AUM. The mean monthly flow for emerging market hedge funds is 0.4 percent. The standard deviation is 1.44, revealing large discrepancies in monthly flows. Once more, the minimum (i.e. the largest monthly outflow) of –3.8 percent occurs during 1998 (October). The highest inflow, 4.2 percent, coincides with Federal Reserve's sudden increase in interest rates in February 1994. The flow for the average non-emerging market fund is twice as high and the volatility is only half of that of emerging market funds. Although the maximum inflow is about the same for the two strategies, the largest outflow for non-emerging market funds is only –0.8 percent, three percentage points less than for emerging market funds.

2.1.3 Factor Return Data

To calculate the systematic component of the returns, returns are regressed on the factors in Fung and Hsieh (2004*b*) with some adjustments. In the main model, the excess return on MSCI World Index (World) is used to represent the market return. The world index includes both developed and emerging markets and hence, it is a good benchmark when comparing the two investment categories. It is also an appropriate benchmark for a well-diversified hedge fund investor.

Other factors are the excess return on a small minus big (SMB) factor constructed as the difference of the Wilshire small and large capitalization stock indices and three portfolios of lookback straddle options on currencies (PTFFX), commodities (PTFCOM) and bonds (PTFBD), all in excess returns. The option factors are constructed to replicate the maximum possible return of a trend-following strategy on the underlying asset. And finally, the yield spread of the U.S. 10-year Treasury bond over the 3-month T-bill, adjusted for the duration of the ten-year bond (BD10), and the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond, also adjusted for duration (BAA).

Two additional models are used for robustness checks. The first model separates the MSCI World Index into the S&P 500 and the MSCI Emerging Market Index. The correlation between the two indices is 0.69. The second model is a pure emerging market model, where equity is represented by the MSCI Emerging Market Index and the long-term bond by the J.P. Morgan Emerging Market Bond Index. All other factors remain the same as in the main model.

3 Methodologies

3.1 Factor Regressions

The risk-adjusted returns are calculated as the intercept when running a regression of hedge fund returns on the modified seven-factor model of Fung and Hsieh (2004*b*). The following equation is estimated:

$$r_{st} = \alpha + \beta X_t + \varepsilon_t \tag{5}$$

where for the main model

$$X_t = [World_t \ SMB_t \ BD10_t \ BAA_t \ PTFBD_t \ PTFFX_t \ PTFCOM_t]. \tag{6}$$

Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors are employed (with six lags).[5]

However, given the changing market conditions during the sample period, managers may have changed their alpha generation tactics over time. Thus,

[5]The analysis is also performed using twelve lags, which does not change the results. Hence, only the results using six lags are reported.

the model is run on three separate periods, largely following Fung et al. (2007). According to Lane and Milesi-Ferretti (2006), global financial integration accelerated in the mid-1990s, suggesting 1998 as the most significant year for a single trend break over 1970 to 2004. Hence, the first break is set to December 1998, allowing the first period to include the Asian and Russian crises as well as the LTCM crisis. The second breakpoint employed is the peak of the technology bubble in March 2000.[6]

3.2 Diversification benefits

Portfolio optimization is used to determine if there are diversification benefits of including emerging market hedge funds in a portfolio of assets. The optimization takes into account the return and risk of the assets as well as any correlation with other assets. A positive weight indicates that the asset is contributing to the performance of the portfolio. The following four assets are included: emerging market and non-emerging market hedge funds, equity, represented by excess return on the MSCI World Index and bonds, represented by the U.S. 10-year Treasury bond. Equity and bonds are included because of the empirical evidence that the weak relationship between hedge fund returns and the returns on other asset classes has a positive effect on portfolio performance.[7]

Four allocation models are used to estimate the portfolio weights to ensure that the results are not driven by assumptions made in a specific model. The models are: Mean-variance portfolio, Bayes-Stein shrinkage portfolio, Optimal "three-fund" portfolio and Bayesian "Data-and-Model" portfolio. A detailed description of the allocation models and the implementation can be found in DeMiguel, Garlappi and Uppal (2007).

The portfolio weights are constrained to be positive and sum to one. Using an expanding window, the portfolio weights are calculated every quarter. Hence, every quarter another three months of historical data are taken into consideration when estimating the required inputs. The choice of an

[6]The validity of the specified breakpoints is tested using the Chow (1960) test.

[7]See Amin and Kat (2003), Schneeweis and Spurgin (1998), Hagelin and Pramborg (2004) and Davies, Kat and Lu (2005).

expanding window is motivated by the short return history of hedge funds, which makes all available data valuable in the estimation.

4 Performance at the Strategy Level

4.1 Univariate Analysis

As a first step, the second panel in Table I compares the return characteristics of emerging market funds to non-emerging market funds. The value-weighted return index for non-emerging funds has a slightly higher average monthly return than emerging market funds (0.51 compared to 0.48 percent) but the standard deviation in the return series is much lower, 1.7 percent as compared to 4.7.

Second, to see the development of the two strategies over time, the cumulative total excess returns are plotted in Figure 1. The figure illustrates that emerging market funds have underperformed non-emerging market funds over the period. An investment of 100 dollars in emerging market funds at the beginning of 1994 was worth 163 dollars at the end of 2004, as compared to 193 dollars for non-emerging market hedge funds.[8] This underperformance is mainly due to the crisis period from the end of 1997 to the end of 1998.

Table II presents the number of live emerging market funds at the end of each year in the dataset, as well as the number of funds that entered and exited the data during the year. The data do not discriminate between funds that exited due to liquidation or because they stopped reporting. However, it seems reasonable to assume that the large percentages of funds exiting in 1998 and 2001 (almost one third of the funds) were liquidated after the crises.

4.2 Risk-adjusted Returns

Figure 1 displays the evolution of total returns. However, the main goal for a hedge fund strategy is to deliver risk-adjusted return, i.e. return

[8]If using equally-weighted portfolios, both portfolios will achieve a higher return, but the relative performance and the patterns over time remain unchanged.

uncorrelated with systemic risk factors. Thus, the hypothesis tested in this section is the following:

Hypothesis 1: *Given hedge funds' flexible investment rules, they should be able to take advantage of investment opportunities in emerging markets and thus generate risk-adjusted returns (alphas).*

To test hypothesis 1, risk-adjusted returns are calculated as the intercept when running a regression of emerging market hedge fund index return on the modified seven-factor model of Fung and Hsieh (2004*b*).

4.2.1 Results Factor Regressions

Table III presents the results from the factor regressions. The first row displays the result from regressing the emerging market strategy return over the entire sample period on the factors. The next three rows are the results from splitting the sample period into the three periods described in section 3.1.

From Panel A in Table III, it is clear that emerging market hedge funds on average have not generated any statistically significant alpha after fees in any period. Hence, the conclusion, which contradicts Hypothesis 1, is that emerging market hedge funds do not create any value above the existing risk factor and thus, the returns can be achieved more cheaply by passive investments. Panel A also presents the results from the factor regressions on non-emerging market funds, which have had a positive and significant alpha in all periods.

Other positive and statistically significant exposures are to the SMB factor and the credit risk factor. Since equity and credit risk factors are proxies for country risk, it is reasonable to assume that this is the main bet taken in emerging market hedge funds. It is interesting that there are no significant exposures to any of the non-linear factors (PTFs).[9] This would indicate that emerging market hedge funds do not use derivatives to any large extent. As a contrast, Chen (2006) finds that 65 percent of the emerging market hedge funds in the TASS database use derivatives. In the databases,

[9]Excluding the option factors does not change the results; emerging market funds do not have a statistically significant alpha in any period.

the managers answer questions on the use of derivatives. However, it is not clear if a positive answer means that they use derivatives (and to what extent) or if they simply have the option to use derivatives.

The analysis in Panel A is performed using net-of-fee returns. It is possible that emerging market funds do have alpha before fees, but that all the rent is extracted by the managers. Using estimated pre-fee returns, the results (shown in Panel B) only change for the last period when the emerging market strategy has a positive and significant alpha. Pre-fee returns are proxied by taking the high watermark and hurdle rate as the T-bill, and assuming that the returns accrue to a first-year investor in the fund.

Even though the alpha in the third period is not statistically significant for emerging market funds when using net-of-fee returns (Panel A), the coefficient is quite large. Panel C in Table III reports the results from substituting the MSCI World Index with the S&P 500 and the MSCI Emerging Market Index. The alpha is then statistically significant in the post-bubble period. The same is true for the pure emerging market model in Panel D. This result is in contrast to the finding in Fung et al. (2007); it is concluded that fund-of-funds' alphas have declined substantially from 2000 until the end of 2004. In Chan, Getmansky, Haas and Lo (2005), it is concluded that the expected returns of hedge funds are likely to be lower and that systemic risk is likely to increase in the future. These factor regressions, however, suggest the opposite trend for emerging market hedge funds.

Regarding the factor loadings, when breaking up the equity factor into the U.S. index and the emerging market index, emerging market funds normally do not have any exposure to U.S. equity (as expected). The exception is in the bubble-period, when the loading on the U.S. equity market is even higher than the exposure to emerging market equity.

Figure 2 displays the cumulative risk-adjusted return over the sample period for both emerging market and non-emerging market funds.[10] The graph confirms the previous findings. Regarding the risk-adjusted returns, emerging market funds have heavily underperformed other funds.

[10]Monthly non-systematic returns are calculated using a rolling twelve-month window over which the factor loadings are calculated. Factor loadings are then multiplied by factor returns and subtracted from total returns to give the non-systematic returns.

4.3 Diversification Benefits

If hedge funds do not generate risk-adjusted returns, there is no reason to pay the high fees charged. However, if the returns of the emerging market funds have a low correlation with other hedge fund strategies or other asset classes, such as equity or bonds, they could be a valuable part of a portfolio. To investigate if this is the case, portfolio optimization is performed using four different allocation models. The hypothesis tested is the following:

Hypothesis 2: *Emerging market hedge funds add value when combined with other assets in a portfolio.*

4.3.1 Results Diversification Benefits

Table IV presents the results from the optimization. The four allocation models all provide the same conclusion: you should not have invested any part of your portfolio in emerging market hedge funds.[11]

The zero investment in emerging markets is not only robust to what allocation model is used, but also over time. Most portfolios have a zero weight on emerging market hedge funds in every quarter of the sample period. There are two exceptions, the mean-variance portfolio and the Bayes-Stein portfolio. However, even for these portfolios, the weight is only positive in four out of 44 quarters analyzed.

Several robustness checks were carried out. The optimization is performed using total returns. The results do not change if the optimization is done using risk-adjusted returns. The outcome also proved robust to the length of the estimation window and to different definitions of the hedge fund strategies (excluding emerging markets). Finally, the result does not change when the adjustment for serial correlation in returns suggested in Getmansky, Lo and Makarov (2004) is performed.[12]

To conclude, the analysis shows that emerging market hedge funds do not offer any benefits that make them valuable in a portfolio. This result contradicts Hypothesis 2 and is not only robust to what allocation model is used but also over time.

[11] The only model that allocates money to emerging market funds on average over the period is the mean-variance portfolio, allocating one percent.

[12] These results are available from the author upon request.

4.4 Investments in Emerging Market Hedge Funds

4.4.1 Investments Relative to the Industry

The previous analysis showed that emerging market funds have performed poorly, both in absolute and relative terms, and that they do not provide any value when included in a portfolio. Hence, the question of interest is to what extent investors have invested in emerging market hedge funds.

Given the short return history of hedge funds and the poor availability of data, investors may have had difficulties evaluating the relative performance of hedge fund strategies. However, as more and better data have become available, investors should have realized that emerging market hedge funds underperform other strategies. For hedge funds, there has also been a shift in investor base, from high net-worth individuals to institutional investors. If the share of sophisticated investors has increased over time, the allocation of money between hedge fund strategies should also have become more efficient. In Eichengreen et al. (1998), it is stated that "some hedge fund experts believe that emerging market hedge funds are the fastest growing segment of the hedge fund industry". In this section, it is investigated if this was in fact the case.

Hypothesis 3: *Over time, hedge fund investors have realized that emerging market funds underperform other strategies and they have reallocated their money away from this strategy.*

Table V presents data on the investments in emerging market hedge funds at a yearly basis. The variables depicted in columns are total assets under management (AUM), number of funds and net capital flows. Figure 3 displays the evolution of AUM and the number of funds on a monthly basis.

Regarding total assets under management, the first column in Table V and the graph in Figure 3 show an increase both at the beginning and at the end of the period. The only large decline in AUM coincides with the Asian and Russian financial crises (as well as the collapse of LTCM). This gives the impression that allocation to emerging market hedge funds only temporarily decreased during the years of financial crises.

However, the second column in Table V presents a different picture. There has been a massive inflow of money into hedge funds during the sample period (see, for example, Fung et al. (2007) and Naik, Ramadorai and Strömqvist (2007)). However, the share of assets under management in emerging market hedge funds in relation to total AUM in the industry has gone from about ten percent during 1994 to 1997 to only a few percent in more recent years.

Concerning the number of emerging market hedge funds, this increased exponentially during the first half of the sample period, peaking with over 200 funds at the end of 1997. However, the number of funds has declined for the latter period. Interestingly, the increase in assets under management during the latter period has not been accompanied by an increase in the number of funds, leading to the conclusion that existing funds have grown substantially during that period. Table V also shows that the share of funds in the hedge fund industry that focuses on emerging markets has decreased from ten percent in 1997 to three percent in 2004.

Since the interest in emerging market hedge funds is ultimately controlled by investors' willingness to allocate capital to this strategy, the last two columns in Table V present the net capital flow into the strategy and its share of total net capital flow into the hedge fund universe. The strategy has had a net capital outflow in four years out of eleven. The share of the industry's net capital flow has become stable around a few percent in the last four years, from being very volatile in the first half of the sample period.

Hence, it appears that investors have indeed learned about the underperformance of emerging market hedge funds over time and, in accordance with Hypothesis 3, have reallocated funds away from this strategy.

4.4.2 Aggregate Capital Flow Determinants

In this section, it is investigated which factors affect capital flows in or out of emerging market hedge funds at the aggregate level. Intuitively, they should broadly depend on two factors: the own-strategy return (in absolute terms and relative to other strategies) and the attractiveness of emerging markets to international investors (relative to the domestic market for these investors).

Hypothesis 4: *Capital flows into the emerging market strategy should be higher if past returns are high, both in absolute terms and relative to other hedge fund strategies. It should also be higher if the attractiveness of the domestic market relative to the foreign market is lower for international investors.*

The main regression model (Model 1) is the following:

$$\begin{aligned} Flow_{EM,t} &= \beta_1 Flow_{EM,t-1} + \beta_2 \operatorname{Re} t_{EM,t-1} + \beta_3 \operatorname{Re} t_{EM,t-2} + \beta_4 \sigma_{EM,t-1} \\ &+ \gamma_1 Flow_{NON,t} + \gamma_2 \operatorname{Re} t_{NON,t-1} + \gamma_3 \operatorname{Re} t_{NON,t-2} \\ &+ \delta_1 US_{t-1} \end{aligned}$$

where the dependent variable is the capital flow to emerging market hedge funds in period t. The flow regression is performed using quarterly data.

Three independent variables relate to the emerging market strategy; past capital flow, past returns and past volatility in returns.[13] There are two independent variables related to the hedge fund industry (excluding emerging market funds); contemporaneous capital flows and past returns. The relationship between emerging market flows and the return on other strategies is expected to be negative, a higher return for non-emerging market funds in past quarters should cause a reallocation from emerging market funds to other funds.

The final independent variable is the quarterly change in the 3-month U.S. T-bill. A decrease (increase) in the interest rate indicates a period of expansive (restrictive) monetary policy. Conover, Jensen and Johnson (2002) show that the benefits of investing in emerging markets accrue during periods of restrictive U.S. monetary policy. They relate the result to the fact that U.S. stock returns tend to be substantially lower in periods when the Federal Reserve is pursuing a restrictive monetary policy.[14] Intuitively, in periods where diversification benefits from investing in emerging markets are greater, the capital flows to these markets will also be greater.

[13] Volatility is calculated as the standard deviation of the past twelve monthly returns.

[14] See Jensen, Mercer and Johnson (1996), Patelis (1997) and Thorbecke (1997). Moreover Conover, Jensen and Johnson (1999) show that the pattern exhibited in the U.S. exists in other developed country markets.

Period dummies are used to control for effects from general trends in the three sub-periods, as specified in section 3.1. Several modifications of Model 1 are performed to test the robustness of the results.

The results for Model 1 in Table VI show that, consistent with previous literature, higher past returns in the strategy have a positive and statistically significant effect on future flows. Higher past returns for non-emerging market funds have a negative impact on future flows into emerging market funds, indicating that investors are concerned with the relative performance of the strategy.

There is a positive and statistically significant effect of contemporaneous capital flow into non-emerging market funds. Thus, an increase of flows into hedge funds in general also boosts flows into emerging market funds, even after controlling for past returns. Including past capital flows into non-emerging market funds (Model 2) does not change the results.

Past own-strategy flows only affect future flows when variables related to non-emerging market funds are excluded (Model 4), consistent with the result in Getmansky (2004). The coefficient on the return volatility in Model 4 is negative and significant, indicating that investors dislike high volatility.[15]

The coefficient on changes in U.S. interest rates is positive and statistically significant. This is consistent with the results in Conover et al. (2002), where the diversification benefits of emerging market investments are larger in periods of restrictive monetary policy in the U.S. It is also consistent with the finding that the highest capital inflow to emerging market hedge funds coincides with the Federal Reserve's increase in interest rates in 1994 (see section 2.1.2).

5 Performance at the Fund Level: Risk-Adjusted Returns and Persistence

The results at the strategy level showed that emerging market hedge funds have performed poorly in terms of risk-adjusted returns and underperformed other strategies. However, that does not exclude the possibility of

[15]Excluding the volatility variable (Model 3) does not change the results.

there being funds that do generate alpha and do so persistently. Thus, the following hypothesis will be tested:

Hypothesis 5: *Emerging market hedge funds only generate risk-adjusted return by luck and hence, there is no persistence in alpha. Thus, funds generating alpha will not have a lower probability of liquidation than other funds.*

5.1 Alpha Determinants

As a first step, a pooled regression is performed to analyze which factors affect the level of risk-adjusted return. The factor realizations are multiplied with loadings estimated over the entire sample period using the modified Fung and Hsieh (2004*b*) model and then subtracted from the fund excess returns. The estimated model is:

$$\begin{aligned} Alpha_{i,t} &= \gamma + \beta_1 Alpha_{i,t-1} + \beta_2 Lock_i + \beta_3 Fee_i + \beta_4 Index_{M,t} \\ &+ \beta_5 Competition_{t-1} + \beta_6 \mathrm{Si}\, ze_{i,t-1} + \beta_7 Age_{i,t-1} \\ &+ \beta_8 \sum_{j=1}^{n} Flow_{i,t-n}. \end{aligned}$$

First, monthly alphas are regressed on past risk-adjusted performance. A positive coefficient on past alpha indicates that there is persistence in alpha. Second, a dummy variable with the value of one if the fund employs lockups and zero otherwise is included. Third, the performance fee is included as an independent variable since it can be considered as an indication of managers' skills. Thus, funds with higher fees should also have higher alpha. Fourth, contemporaneous excess return on the MSCI Emerging Market Index is used as a proxy for market conditions.

Additional explanatory variables are competition (proxied by the number of funds in the strategy last month), fund size, age (as in the number of months the fund has been in the sample) and the cumulative net capital flows into the fund during the last six months. The analysis only considers the level of alpha and not whether the alpha is statistically significant.

The results are shown in Table VII.[16] There is a statistically significant and positive relationship between current and past alpha, indicating that there is some persistence in returns. However, the coefficient is small; an alpha of one percent in the previous period will, on average, generate an alpha of ten basis points in the next period.

There is also a strong positive correlation with the current return on the MSCI Emerging Market Index, suggesting that funds perform better when the return on the stock market is high. This can partly be explained by the large loadings of these funds on equity, as previously shown. As a robustness test, the return on the MSCI Emerging Market Index is substituted with a dummy variable with the value of one for those months that have a return in the top 20 percent of the distribution over the sample period, and zero otherwise. The results are then even stronger, with a coefficient on the market return that is more than eight times as large as the past alpha coefficient. This indicates that contemporaneous market conditions are more important than past performance for predicting alpha.

Funds employing lockups perform better, which is consistent with the findings in Aragon (2007). And higher competition has a negative effect on performance, as in Getmansky (2004). The results also reveal that younger funds tend to perform better than older funds. Previous literature (see, for example, Fung and Hsieh (1997*b*)) has argued that reputation costs have a mitigating effect on the incentives to take on risks for older funds. In accordance with the results in Naik et al. (2007), capital inflows have a negative effect on the risk-adjusted performance. Naik et al. (2007) conclude that the negative flow-performance relationship is due to capacity constraints. Finally, there are no effects from fund size or the level of performance fee.

The results are robust to different specifications of the model and whether period dummies and/or focus area dummies are used, as can be seen in Table VII.

5.2 Transition Probabilities

Instead of analyzing the level of risk-adjusted return, this section investigates how many funds that have a statistically significant alpha and if

[16]The results are robust to adjusting returns for serial correlation.

these funds have a higher probability than other funds of creating value also in the next period. The analysis is performed following the methodology in Fung et al. (2007), with some modifications. The alpha is estimated as the intercept from running the modified Fung and Hsieh (2004*b*) model over 18 months of data for each fund separately. Hence, only funds with monthly returns throughout the entire period in question are used. The funds are then classified as Alpha or Beta funds using the t-statistic of the intercept. To make the analysis more robust, the t-statistics are cross-sectionally bootstrapped as in Fung et al. (2007).

The results can be found in Table VIII. On average, 89 percent of the funds do not have a statistically significant alpha.[17] Hence, in most periods, less than 10 percent (15 funds) are classified as Alpha funds.[18] The exception is the period from July 2000 to June 2003. This supports the previous result that emerging market hedge funds tend to mainly generate risk-adjusted return when the return on the stock market is high.

Regarding the transition probabilities, the probability of an Alpha fund also creating value in the next period is 26 percent. Although it is not a high number, it is high compared to the probability for other funds (7 percent). This indicates that Alpha funds do exhibit some persistence in performance. Alpha funds also have a lower probability of liquidation than other funds (13 percent as compared to 26 percent). The results are comparable to those in Fung et al. (2007), where it is found that Alpha funds have twice as high probability as Beta funds of being Alpha funds in the next period.

5.3 Liquidation Probabilities

The liquidation of a fund will intuitively depend on different fund characteristics, such as past returns, asset size and age. Getmansky (2004) also finds that it can depend on the level of competition within the strategy. A logit model of the probability of liquidation is specified to investigate the

[17] Almost no funds are classified as having a negative alpha. The exception is in the crisis period from mid 1997 to the end of 1998, when 13 percent of the funds had a negative alpha. This indicates that the factor model does not capture the extreme liquidity risk during this period.

[18] Using fund-of-funds, Fung et al. (2007) find in their analysis that 22 percent of the funds are classified as having alpha.

factors that affect the liquidation probability for emerging market hedge funds

$$Liquidation_{i,t} = f(\gamma_{i,t} + \beta_1 Age_{i,t} + \beta_3 Alpha_{i,t} + \beta_4 Alpha_{i,t-1} + \beta_5 Alpha_{i,t-2} + \beta_6 \,\mathrm{Si}\, ze_{i,t-1} + \beta_7 Competition_{i,t-4}).$$

The variables used are current age, current alpha and the alpha during the past two quarters. Additional explanatory variables are size (measured as the natural logarithm of assets under management) and the number of hedge funds in the strategy a year before as a proxy for competition. The model also incorporates period-fixed effects.

Table IX presents the findings. The main result is that the probability of being liquidated is lower for larger funds that performed well during the last two quarters. However, the probability of being liquidated is greater if competition is higher.[19] There is no significant effect of the age of the fund. These results are largely consistent with the findings in Getmansky (2004).

5.4 Alpha and Beta Funds

In this section, funds are sorted into two categories (Alpha and Beta funds) depending on the t-statistic of the alpha estimated over the previous period. As in section 5.2, the alpha is the intercept when running the modified Fung and Hsieh (2004*b*) model on the returns of the past eighteen months. Two portfolios are formed by weighting the funds equally and are then held for twelve months before being re-weighted. To handle exiting funds, the weights are re-calculated within the portfolios each month during the holding period. The purpose of the analysis is to investigate if there are funds that perform persistently well.

[19] Getmansky (2004) argues that a year lag should be taken when calculating competition because it takes some time for hedge funds to become competitive. However, for emerging market hedge funds, the result is the same if only one quarterly lag is used.

5.4.1 Performance

Table X presents monthly average total and risk-adjusted returns for the two portfolios and the spread between them. Alpha funds have a significantly higher return (total as well as alpha) than Beta funds and lower standard deviations. This indicates that, on average over the period, Alpha funds outperform Beta funds.

Figure 4 displays the cumulative risk-adjusted returns for the Alpha and Beta portfolios from April 1996 to December 2004. The two portfolios have a similar return up until 2002, after which Alpha funds outperform Beta funds.[20] Over the entire period, Alpha funds generate a return that is about 40 percent higher than Beta funds. Figure 4 also shows that the Alpha funds are less volatile and hence, offer some protection during the crisis periods.[21]

5.4.2 Diversification Benefits

The optimization performed in section 4.3 showed that there are no diversification benefits from including emerging market hedge funds in a portfolio of assets. The question is if the result holds for the portfolio of Alpha funds. Thus, the optimization is once more performed, but this time with Alpha and Beta funds for emerging market funds as two separate assets.

Table XI presents the result. Interestingly, these few emerging market Alpha funds dominate other hedge funds. Thus, adding these funds to your portfolio will benefit your risk-return relationship. The average portfolio weight in Alpha funds is about 50 percent, with less than one percent in other hedge fund strategies, a few percent in equity and about 40 percent in long-term bonds. The weight on Beta funds is zero. Hence, the negative performance of emerging market hedge funds at the strategy level is driven by the large numbers of Beta funds.

It is also interesting that the initial weight in Alpha funds is zero, but the final weight is over 70 percent for the Mean-Variance and the Bayes-Stein

[20] There is no difference between Alpha and Beta funds if a two-year holding period is implemented.

[21] The results are robust to adjusting the returns for serial correlation. Moreover, Alpha funds still outperform Beta funds if value-weighted portfolios are used.

portfolios. This is consistent with the finding that there is only persistence in performance in the latter half of the sample period.

5.4.3 Net Capital Flows to Alpha and Beta Funds

Given that there is a significant difference between the performance of Alpha and Beta funds, it is of interest to examine if investors have been able to separate between the two categories. If so, Alpha funds should have received more capital inflows than Beta funds. Regarding fund-of-funds, Fung et al. (2007) find that investors can make the separation between Alpha and Beta funds. However, it is reasonable to assume that it is more difficult to differentiate between individual funds, especially regarding investments in emerging markets.

Figure 5 plots the cumulative net capital flow to the two groups over time. Contrary to the above reasoning, Beta funds have had a greater capital inflow than Alpha funds.[22] This was especially the case in the crisis period between 1997 and the end of 1999. Hence, investors cannot differentiate between the two groups.

6 Discussion

The results in this paper indicate that there is only a handful of emerging market managers that are able to deliver risk-adjusted returns. However, there are several potential reasons for this outcome. In this section, factors unrelated to manager skills that may affect the performance are discussed.

It may be the case that the small size and illiquidity of emerging markets prevent skillful managers from generating superior returns. Lesmond, Ogden and Trzcinka (1999) argue that if the value of an information signal is insufficient to outweigh the costs associated with transacting, then market participants will not trade. Hence, emerging market hedge fund managers may be able to identify investment opportunities, but refrain from acting on them as they estimate the cost of trading to be greater than the potential profits. And if they still do act on them, despite the high costs, any profit generated in the end will be small.

[22]The results do not change if value-weighted portfolios are used.

The liquidity is also lower in emerging markets due to short-selling constraints. In a paper by Bris, Goetzmann and Zhu (2007), it is shown that short-selling is, if not prohibited, very limited in most emerging countries. Thus, hedge funds may not be able to go short to take advantage of inefficiencies in emerging markets, which could have a negative effect on their returns. Even if short-selling is restricted, it is still possible to go short in the market using GDRs/ADRs, single stock futures or index derivatives, although maybe not to the same degree as if short-selling were widely practiced in the market.

The persistence in performance in the last three years studied coincides with a boom-market for emerging markets. There are two interpretations of this result (which are not mutually exclusive).

The first, which is supported by the positive correlation between alpha and return on the MSCI Emerging Market Index, is that there is only persistence in boom-markets. In bear markets, the liquidity generally goes down, which intuitively hurts emerging markets more than developed markets since the liquidity is relatively low to begin with. In this case, it is important to time the market conditions when investing in emerging market funds.

The other is that there has been a general improvement in liquidity in emerging markets in the latter period, perhaps due to increased globalization. This would have enhanced the possibility for skillful managers to perform consistently well. Emerging market hedge funds may then persistently generate value in the future, given that this trend continues.

And finally, the underperformance of emerging market funds compared to other strategies could be due to self-selection amongst managers. There are two reasons for this. First, since there are several institutional features of emerging markets that make it difficult to generate risk-adjusted returns, skillful managers may choose other strategies. Their talent would be more visible in other strategies, which would mean higher utility for the manger. Second, for emerging market hedge funds, good performance (in terms of risk-adjusted returns) is not rewarded with capital inflows. This reduces the incentives for managers to exert effort, take risky bets and may even deter skillful managers from entering the strategy.

7 Conclusions

This paper investigates the performance and capital flows of emerging market hedge funds during 1994 to 2004.

At the strategy level, the results reveal that emerging market hedge funds have, on average, only been able to provide a risk-adjusted return during the most recent period between 1994 and 2004. Moreover, emerging market hedge funds do not offer any diversification benefits when combined with other assets in a portfolio. Despite the underperformance of these funds in terms of alpha, they have received an almost exponential inflow in the most recent years. However, the strategy's share of the hedge fund industry's total capital flows has decreased significantly during the same period, thus indicating that investors have reallocated their money from emerging market hedge funds to other hedge fund strategies.

At the fund level, it is discovered that there are a few emerging market funds that create value and that there is weak persistence in performance at the one-year horizon. This is mainly true in bull markets, however. Since good performance (in terms of risk-adjusted returns) is not rewarded with capital inflows, managers' incentives to exert effort and take risky bets are reduced. It may even deter skillful managers from entering the strategy, partly explaining the poor performance at the strategy level.

Although the emerging market strategy has performed poorly in the past, the upward trend in performance over time is an important finding. Given that other hedge fund strategies have a declining trend in alpha, emerging market funds might be where future alphas can be found.

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Table I
Summary Statistics

This table presents summary statistics for emerging market and non-emerging market hedge funds in the sample. The first panel displays, in rows, the number of funds in the sample, the average life in years, average fund AUM, the average (value-weighted) performance fee and the percentage of funds that employ lockups. The two following panels show summary statistics for the monthly value-weighted hedge fund index returns (in excess over the three-month U.S. Treasury bill) and the monthly net flows as a percentage of strategy AUM, respectively. The summary statistics presented in rows are the mean, median, standard deviation, minimum and maximum.

Summary Statistics	**Emerging Markets**	**Non-Emerging Markets**
Number of funds	418	7,187
Average life in years	4.4	4.5
Average AUM (US $MN)	75.6	100.6
Value-weighted performance fee (%)	17.7	18.4
Funds with lockups (%)	11	24
Excess return (%)		
Mean	0.48	0.51
Median	1.18	0.48
Standard deviation	4.73	1.72
Minimum	-22.71	-5.65
Maximum	15.04	5.77
Flows (%)		
Mean	0.40	0.84
Median	0.44	0.80
Standard deviation	1.44	0.76
Minimum	-3.83	-0.82
Maximum	4.22	4.20

Table II
Funds Entering and Exiting the Sample

For each year represented in a row, this table presents the number of funds in the data at the end of each year, the number of funds that entered the data during the year and the number of funds that exited the data during the year.

Year	Number of Funds End of Year	Entered (%)	Exited (%)
1995	129	51	5
		(61%)	(6%)
1996	182	69	16
		(53%)	(12%)
1997	209	68	41
		(37%)	(23%)
1998	195	47	61
		(22%)	(29%)
1999	188	29	36
		(15%)	(18%)
2000	173	25	40
		(13%)	(21%)
2001	129	5	49
		(3%)	(28%)
2002	128	10	11
		(8%)	(9%)
2003	132	26	22
		(20%)	(17%)
2004	124	4	12
		(3%)	(9%)

Table III
Factor Regressions

This table presents results from regressing monthly hedge fund strategy index returns on the modified Fung and Hsieh (2004b) model. The left hand-side variable in each regression is the AUM weighted (net-of fees) excess return of the hedge fund strategy. The seven right hand-side variables in Panel A are excess return on the MSCI World Index (World); a small minus big (SMB) capitalization factor; excess returns on three portfolios of lookback straddle options (PTFs) on bonds, commodities and foreign exchange; the spread of Moody's BAA corporate bond returns index over the U.S. 10 year maturity Treasury bond (BAA spread), and finally the excess return of the U.S. 10-year maturity Treasury bond. Panel B displays the results for estimated pre-fee returns for emerging market hedge funds. In Panel C the MSCI World Index has been replaced by the MSCI Emerging Market Index (MSCI EM) and the S&P 500 (SNP). The pure emerging market model in Panel D has the same variables as in Panel A except that equity and bond indices are emerging market indices (MSCI Emerging Market Index and J.P. Morgan Emerging Markets Bond Index). All excess returns are over the U.S. 3-month Treasury bill rate. For each period represented in a row, the columns present the intercept (alpha), the slope coefficients on the seven factors and the adjusted R-square. Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors are employed (6 lags). Significance at the one, five and ten percent level is given by ***, ** and * respectively.

As indicated in rows, the regression is performed first on overall sample and then on three sub-periods; January 1994 to December 1998 (Period I: Asian, Russian and LTCM crises), January 1999 to March 2000 (Period II: Bubble period) and April 2000 to December 2004 (Period III: Post-bubble period).

The last two columns present the result from testing for two sample breaks; between period I and period II and between period II and period III. Test for structural breaks using the dummy variant of the Chow (1960) test is applied only to slope coefficients, not constant term. The value of the F-statistic is shown in the table below and the critical value (alpha=0.05) is 2.167.

Panel A: World Model

Returns	α	World	SMB	PTF Bonds	PTF Com	PTF FX	BAA Spread	TCM 10 Y	R^2	I=II?	II=III?
Emerging Market											
Overall period	0.135	0.644***	0.321***	-0.033	-0.001	0.003	0.604**	0.134	0.490		
Period I	-0.800	0.781***	0.243	-0.042	0.009	0.002	1.484**	-0.043	0.455	1.011	2.474**
Period II	0.748	1.232**	0.504***	0.031	-0.030	-0.002	0.128	-0.823	0.735		
Period III	0.544	0.538***	0.230**	0.002	0.041	-0.002	0.418*	0.298**	0.670		

Table III continued

Returns	α	World	SMB	PTF Bonds	PTF Com	PTF FX	BAA Spread	TCM 10 Y	R^2	I=II?	II=III?
Non-Emerging Markets											
Overall period	0.387***	0.252***	0.148***	-0.008	0.017	0.012*	0.155	0.198***	0.541		
Period I	0.465***	0.263***	0.163**	-0.016	0.037**	0.012	0.516*	0.300***	0.500	3.157***	17.719***
Period II	0.459***	0.366***	0.303***	0.035**	-0.017***	-0.002	0.390	0.223	0.967		
Period III	0.205***	0.194***	0.122***	0.000	0.016**	0.010*	0.069	0.138***	0.737		

Panel B: Pre-Fee Returns

Returns	α	World	SMB	PTF Bonds	PTF Com	PTF FX	BAA Spread	TCM 10 Y	R^2
Emerging Market									
Overall period	0.270	0.573***	0.303***	-0.032	0.018	0.006	0.560**	0.111	0.454
Period I	-0.616	0.713***	0.225	-0.039	0.022	0.005	1.280*	-0.093	0.414
Period II	0.946	1.163**	0.459***	0.019	0.017	0.039	0.364	-0.580	0.587
Period III	0.674**	0.493***	0.162**	0.003	0.037	-0.002	0.368*	0.289**	0.638

Panel C: U.S. and Emerging Market Model

Returns	α	MSCI EM	SMB	PTF Bonds	PTF Com	PTF FX	BAA Spread	TCM 10 Y	SNP	R^2
Emerging Market										
Overall period	0.489	0.622***	0.066	-0.031*	0.012	0.008	0.307	0.189**	-0.069	0.792
Period I	0.495	0.672***	0.122	-0.032**	0.014	0.012	1.759***	0.294*	-0.143	0.833
Period II	0.117	0.580***	0.409***	0.050	0.012	0.038	0.369	-0.033	0.603***	0.958
Period III	0.549**	0.481***	0.041	-0.005	0.034**	0.003	0.068	0.240**	0.050	0.872

Table III continued

Panel D: Pure Emerging Market Model									
Returns	α	MSCI EM	SMB	PTF Bonds	PTF Com	PTF FX	BAA Spread	JPM EM Bond Index	R^2
Emerging Market									
Overall period	0.445	0.589***	0.091	-0.031*	0.012	0.008	0.289	0.181**	0.779
Period I	0.243	0.615***	0.126	-0.026**	0.015	0.009	1.739***	0.188	0.806
Period II	0.412	0.771***	0.280***	0.145**	0.012	-0.033	1.156*	1.125**	0.854
Period III	0.543**	0.511***	0.026	-0.006	0.034**	0.003	0.076	0.224**	0.852

Table IV
Portfolio Optimization: Strategy Level

This table presents results from optimizing over returns on four assets: emerging market hedge funds, non-emerging market hedge funds, equity (MSCI World Index) and bonds (U.S. 10-year maturity Treasury bond). All returns are monthly excess returns over the 3-month U.S. Treasury bill. The portfolio weights are constrained to be between zero and one and to sum to one. The optimization is performed using an expanding window and the weights are estimated quarterly during 1994 to 2004. In the table below the mean weight over this period, the standard deviation, the initial and ending weights are indicated in rows for the portfolios. Four different optimization models are used: Mean-variance portfolio, Bayes-Stein shrinkage portfolio, Optimal 3-fund portfolio (Kan and Zhou (2005)) and Bayesian Data-and-Model Portfolio (Pastor (2000), Pastor and Stambaugh (2000)), as indicated in columns.

Weights	**Mean-Variance**	**Bayes-Stein**	**3-fund**	**Data&Model**
Mean				
Emerging markets	0.01	0.00	0.00	0.00
Non-Emerging markets	0.94	0.92	0.90	0.88
Equity	0.01	0.02	0.02	0.03
Bonds	0.04	0.06	0.08	0.09
Standard deviation				
Emerging markets	0.02	0.00	0.00	0.00
Non-Emerging markets	0.03	0.02	0.02	0.03
Equity	0.02	0.02	0.02	0.03
Bonds	0.03	0.05	0.07	0.06
Initial weight				
Emerging markets	0.08	0.03	0.00	0.00
Non-Emerging markets	0.87	0.87	0.85	0.79
Equity	0.00	0.02	0.04	0.00
Bonds	0.05	0.08	0.11	0.21
Final weight				
Emerging markets	0.00	0.00	0.00	0.00
Non-Emerging markets	0.95	0.92	0.91	0.89
Equity	0.00	0.00	0.00	0.00
Bonds	0.05	0.08	0.09	0.11

Table V
Investments in Emerging Market Hedge Funds

This table presents the assets under management (AUM), number of funds and net capital flows in emerging market hedge funds each year and the respective share of the same for emerging market hedge fund strategy in the hedge fund industry.

	AUM		Number of Funds		Net Flows	
Year	**Emerging (US $BN)**	**% of industry**	**Emerging**	**% of industry**	**Emerging (US $BN)**	**% of industry**
1994	7.26	10%	83	7%	1.09	35%
1995	7.92	9%	129	9%	-0.25	-48%
1996	11.90	9%	182	9%	0.54	6%
1997	19.55	10%	209	10%	2.45	10%
1998	9.25	4%	195	8%	-0.91	-5%
1999	11.29	4%	188	7%	-1.09	-12%
2000	8.58	3%	173	6%	-0.23	-1%
2001	8.28	2%	129	4%	0.03	0%
2002	9.78	2%	128	3%	0.65	2%
2003	15.19	3%	132	3%	1.67	2%
2004	22.32	3%	124	3%	3.59	4%

Table VI
Aggregate Flow Determinants

This table reports the results from regressing quarterly flows for emerging market hedge funds on past quarterly flows, past quarterly returns and the standard deviation of 12 monthly returns for emerging market funds. Other independent variables are contemporary and past quarterly flows and past quarterly returns for non-emerging market funds and the quarterly change in the U.S. interest rate. The standard errors have been calculated using robust standard errors [Newey and West (1987) with 4 lags]. T-statistics are given in parenthesis and significance at the one and five percent level is indicated by *** and **, respectively. Period dummies for the three periods are used (Period I: Asian, Russian and LTCM crises, Period II: Bubble period and Period III: Post-bubble period). The adjusted R-square is presented in parenthesis with the corresponding R-square when the model is estimated without fixed effects in brackets underneath.

Dependent variable: $Flow_{EM,t}$	Model 1	Model 2	Model 3	Model 4
$Flow_{EM,t-1}$	0.007	-0.030	0.086	0.103**
	(0.06)	(-0.20)	(0.81)	(1.72)
Return $_{EM,t-1}$	0.188***	0.184**	0.192**	0.233***
	(2.84)	(2.49)	(2.55)	(3.59)
Return $_{EM,t-2}$	0.195***	0.211***	0.211***	0.050
	(2.92)	(2.90)	(3.13)	(0.21)
$\sigma_{EM,t-1}$	0.020	0.012		-0.255**
	(0.16)	(0.11)		(-2.45)
$Flow_{NON-EM,t}$	0.836***	0.776***	0.666***	
	(4.96)	(5.02)	(7.59)	
$Flow_{NON-EM,t-1}$		0.124		
		(0.93)		
Return $_{NON-EM,t-1}$	-0.085	-0.080	-0.009	
	(-0.33)	(-0.29)	(-0.04)	
Return $_{NON-EM,t-2}$	-0.973***	-1.019***	-0.979***	
	(-5.23)	(-5.57)	(-0.33)	
Δ US interest rate	8.456***	8.116***		
	(3.63)	(3.87)		
$Adj\ R^2$	0.672	0.664	0.638	0.462
	[0.434]	[0.416]	[0.441]	[0.275]
Period fixed effects	Yes	Yes	Yes	Yes

Table VII
Pooled Performance Regression

This table reports the results from regressing monthly alphas for emerging market hedge funds on past alpha, a dummy with the value one if the fund employs lockups and zero otherwise, performance fee, contemporaneous return on the MSCI Emerging Market Index, past fund size in logarithmic the number of funds in the strategy last months as a proxy for competition, past fund size in logarithmic values, age as the number of months the fund has been in the sample and the past three months' net capital flows into the fund. As an alternative to the return on the MSCI Emerging Market Index, a dummy variable is constructed with the value one if the return on the index is in the top 20 percent over the sample period and zero otherwise. Monthly alphas are calculated as fund excess returns minus the factor realizations times loadings estimated over the entire sample period using the modified Fung and Hsieh (2004) model. T-statistics are given in parenthesis and significance at the one, five and ten percent level is indicated by ***, ** and *, respectively. The adjusted R-square is presented in the next row. Period dummies for the three periods are used as well as dummies for investment focus areas.

Dependent variable: *$Alpha_t$*	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$Alpha_{t-1}$	0.108***	0.108***	0.108***	0.117***	0.117***	0.171**	0.170 **
	(6.30)	(6.28)	(6.51)	(7.04)	(7.06)	(2.27)	(2.25)
Lockup dummy	0.572***	0.576***	0.576***	0.665***	0.674***	0.500***	0.501***
	(3.08)	(3.12)	(3.14)	(3.59)	(3.62)	(2.79)	(2.80)
Performance fee	0.011	0.011					
	(1.15)	(1.13)					
$Market\ return_t$	0.149***	0.149***	0.150***	0.172***	0.172***	0.156***	
	(13.18)	(13.16)	(13.60)	(15.44)	(15.53)	(12.73)	
Market top 20% dummy							1.408***
							(7.40)
$Competition_{t-1}$	-0.010***	-0.010***	-0.010***	-0.008***	-0.008***	-0.005**	-0.009***
	(-5.37)	(-5.41)	(-5.83)	(-5.02)	(-4.96)	(-2.22)	(-4.33)
$Fund\ size_{t-1}$	-0.006	-0.007					
	(-0.14)	(-0.15)					
$Fund\ age_{t-1}$	-0.225**	-0.223**	-0.225**	0.008		-0.265**	-0.247**
	(-2.23)	(-2.20)	(-2.33)	(1.01)		(-2.39)	(-2.22)
$\sum FundFlow_{t-n}$	-0.001	-0.001	-0.001	-0.002**	-0.002**		
	(-1.43	(-1.43)	(-1.44	(-2.05)	(-2.05)		
Adj R^2	0.050	0.050	0.051	0.043	0.043	0.057	0.048
Period fixed effects	Yes	Yes	Yes	No	No	Yes	Yes
Focus area dummy	Yes	No	No	No	Yes	No	No

Table VIII
Transition Probabilities

The rows show the 18-month period in which funds are classified as Alpha and Beta funds. The classification is made depending on the t-statistic of the intercept when running the modified Fung and Hsieh (2004b) model on the funds' return series. The t-statistics are bootstrapped cross-sectionally using the methodology in Fung et al. (2007). The columns are, in order: the total number of funds with 18 months of return history in each of the classification periods; the percentages of total classified as Alpha and Beta funds; the percentages within each classification group that are classified in the subsequent period as Alpha or Beta funds or which exited the sample. The Wald statistic is based on testing whether the transition probabilities differ between Alpha and Beta funds.

Period	Number of funds	Alpha	Beta	From/To:	Alpha	Beta	Exited
1994:7-1995:12	68	0.04	0.96	Alpha	0.33	0.67	0.00
				Beta	0.02	0.77	0.21
1996:1-1997:6	123	0.07	0.93	Alpha	0.22	0.33	0.44
				Beta	0.02	0.61	0.36
1997:7-1998:12	140	0.06	0.94	Alpha	0.50	0.38	0.13
				Beta	0.06	0.72	0.22
1999:1-2000:6	149	0.09	0.91	Alpha	0.38	0.46	0.15
				Beta	0.16	0.49	0.36
2000:7-2001:12	121	0.26	0.74	Alpha	0.29	0.55	0.16
				Beta	0.13	0.74	0.14
2002:1-2003:6	111	0.19	0.81	Alpha	0.10	0.86	0.05
				Beta	0.04	0.71	0.24
2003:7-2004:12	114	0.09	0.91				
Average		0.11	0.89	Alpha	0.26	0.46	0.13
				Beta	0.07	0.67	0.26
				Wald Statistic	23.88	8.26	8.79
				p-value	0.00	0.00	0.00

Table IX
Liquidation Probability

The table displays the results from a logit regression on probability of liquidation for emerging market hedge funds at time *t* on intercept, current age, current and past quarterly risk-adjusted returns (alpha), previous assets under management in logarithmic values and the number of funds in the previous year as a proxy for competition. Coefficients and standard errors are multiplied with 100 for display purposes. Period dummies for the three periods are used (Period I: Asian, Russian and LTCM crises, Period II: Bubble period and Period III: Post-bubble period). Significance at the one and five percent level is indicated by ***, and **, respectively.

Dependent variable: *Liquidation dummy$_t$*	**Estimate**	**Std. Error**	**Wald Chi-Square**	**Pr > Chi-Square**
Intercept	-236.210***	12.50	356.050	0.000
Fung age$_t$	-0.043	0.253	0.029	0.865
Alpha$_t$	-0.710***	0.276	6.602	0.010
Alpha$_{t-1}$	-1.480***	0.280	27.876	0.000
Alpha$_{t-2}$	-0.106***	0.282	14.059	0.000
Assets$_{t-1}$	-3.910***	1.300	8.996	0.003
Competition$_{t-4}$	0.129**	0.067	3.732	0.050
Period dummies	Yes	R-Square	0.05	

Table X
Equally-Weighted Portfolios of Alpha and Beta Funds

This table presents, in columns, the mean total return and risk-adjusted return (alpha) with respective standard deviations for equally-weighted portfolios of Alpha and Beta funds, in rows. The alpha is defined as the intercept when regression 18 months of returns on the modified model of Fung and Hsieh (2004b). Funds are then sorted into Alpha and Beta funds depending in the t-statistic of the intercept. The two equally-weighted portfolios are then held for 12 months before being re-weighted. The last row in each column displays the spread between the two portfolios. Statistically significant spreads at the five percent level are market with **.

Panel A: Excess Returns				
Total Returns	**Mean Total Return**	**Std. dev**	**Mean Alpha**	**Std. dev**
Alpha Funds	1.28	3.48	0.44	4.08
Beta Funds	0.83	5.29	0.25	6.30
Spread	0.45**	-1.81**	0.19**	-2.22**

Table XI
Portfolio Optimization with Alpha and Beta Funds

This table presents results from optimizing over returns on five assets: emerging market Alpha and Beta funds, non-emerging market hedge funds, equity (MSCI World Index) and bonds (U.S. 10-year maturity Treasury bond). All returns are monthly excess returns over the 3-month U.S. Treasury bill. The groups of Alpha and Beta funds are based on the portfolio strategy of classifying funds by regressing 18-months excess return on the modified Fung and Hsieh (2004b) model, sorting funds by the t-statistic of the intercept and then holding the two equally-weighted portfolios for 12 months before re-weighting them. The optimization is performed using an expanding window and the weights are estimated quarterly during July 1995 to December 2004. The portfolio weights are constrained to be between zero and one and to sum to one. In the table below the mean weight over this period, the standard deviation, the initial and ending weights are indicated in rows for both portfolios. Four different optimization models are used, as indicated in columns.

Weights	**Mean-Variance**	**Bayes-Stein**	**3-fund**	**Data&Model**
Mean				
Emerging markets Alpha funds	0.505	0.508	0.496	0.422
Emerging markets Beta funds	0.000	0.000	0.000	0.000
Non-Emerging markets	0.006	0.005	0.005	0.004
Equity	0.035	0.029	0.030	0.061
Bonds	0.453	0.458	0.469	0.513
Standard deviation				
Emerging markets Alpha funds	0.186	0.183	0.180	0.159
Emerging markets Beta funds	0.002	0.000	0.001	0.001
Non-Emerging markets	0.020	0.018	0.017	0.014
Equity	0.074	0.058	0.046	0.080
Bonds	0.118	0.126	0.136	0.097
Initial weight				
Emerging markets Alpha funds	0.000	0.000	0.000	0.000
Emerging markets Beta funds	0.000	0.000	0.000	0.000
Non-Emerging markets	0.094	0.085	0.075	0.063
Equity	0.199	0.178	0.153	0.216
Bonds	0.707	0.736	0.772	0.722
Final weight				
Emerging markets Alpha funds	0.732	0.711	0.613	0.387
Emerging markets Beta funds	0.000	0.000	0.000	0.000
Non-Emerging markets	0.000	0.000	0.000	0.000
Equity	0.000	0.000	0.045	0.146
Bonds	0.268	0.289	0.343	0.467

Figure 1: Cumulative Total Returns

The figure plots the cumulative total value-weighted return indices of the emerging market strategy and all other hedge funds. The data begin in the first month of 1994 and end in the final month of 2004.

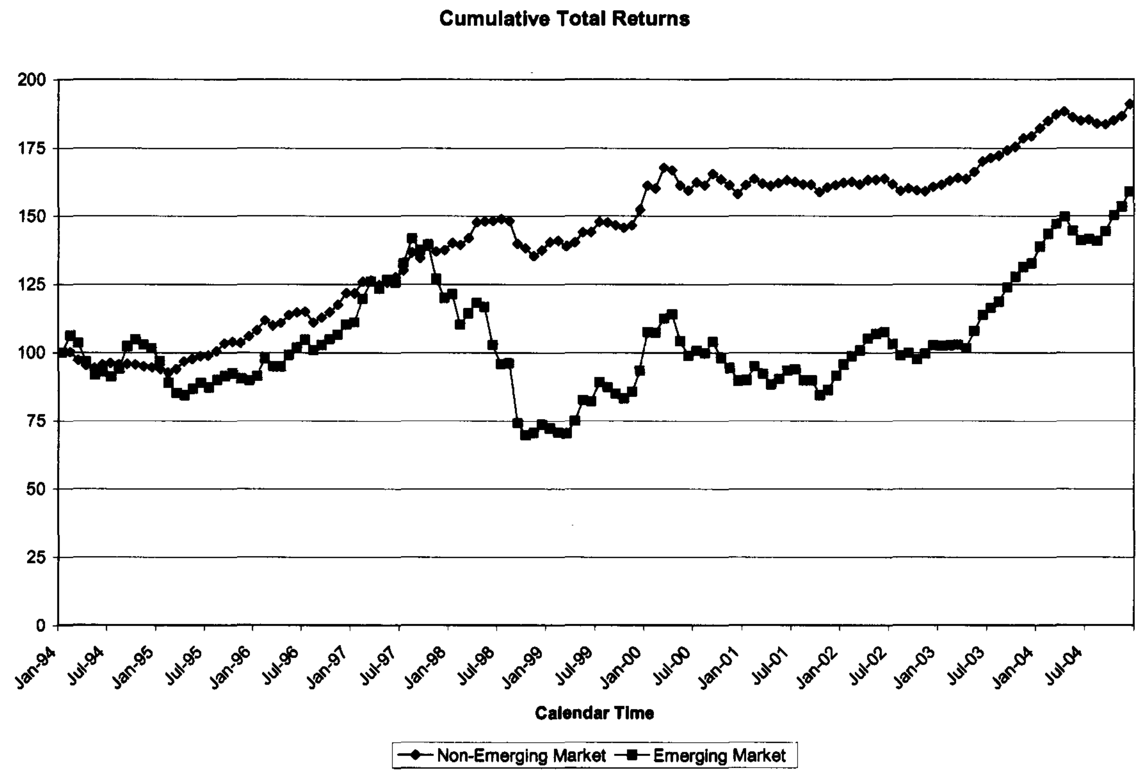


Figure 2: Cumulative Risk-Adjusted Returns

The figure plots the cumulative risk-adjusted value-weighted return indices of emerging market hedge fund and all other hedge funds. The data begin in April 1994 and end in December 2004.

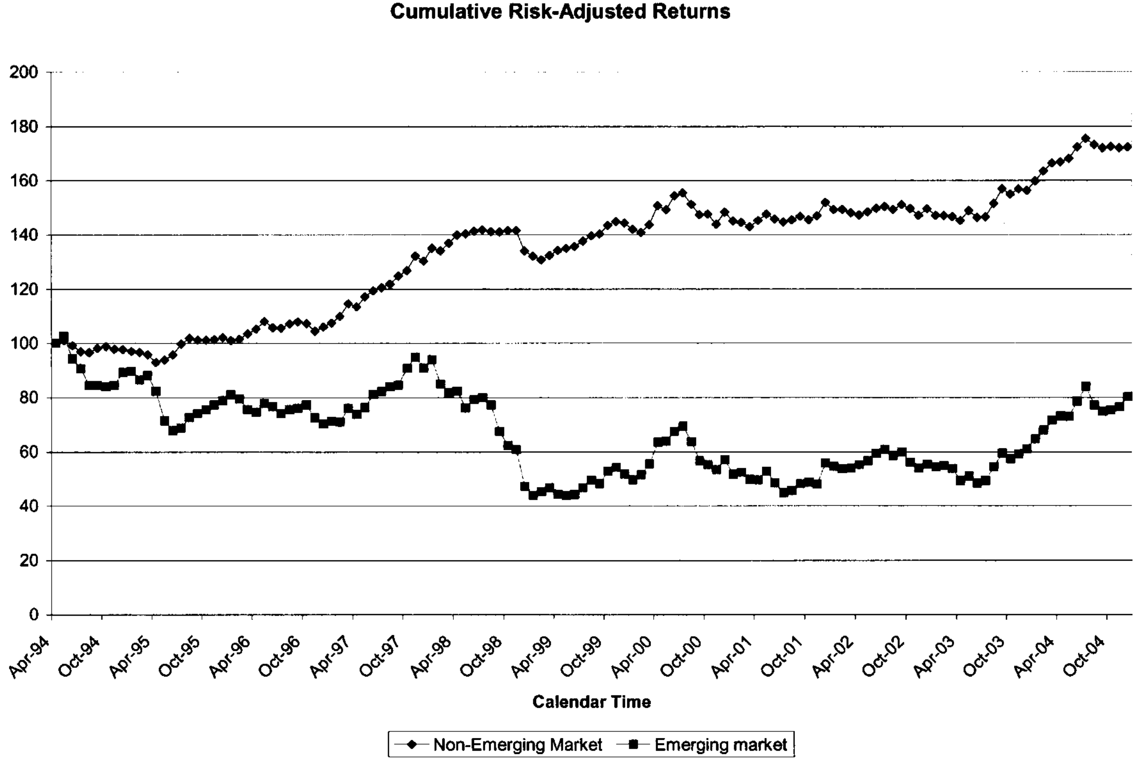


Figure 3: Number of Funds and Total AUM

This figure plots the evolution of the number of emerging market hedge funds and the total assets under management (AUM) contained in the strategy in the sample across time measured in months. The data are constructed by aggregating information from TASS, HFR, CISDM and MSCI for funds that report AUM. The data begin in the first month of 1994, and end in the final month of 2004.

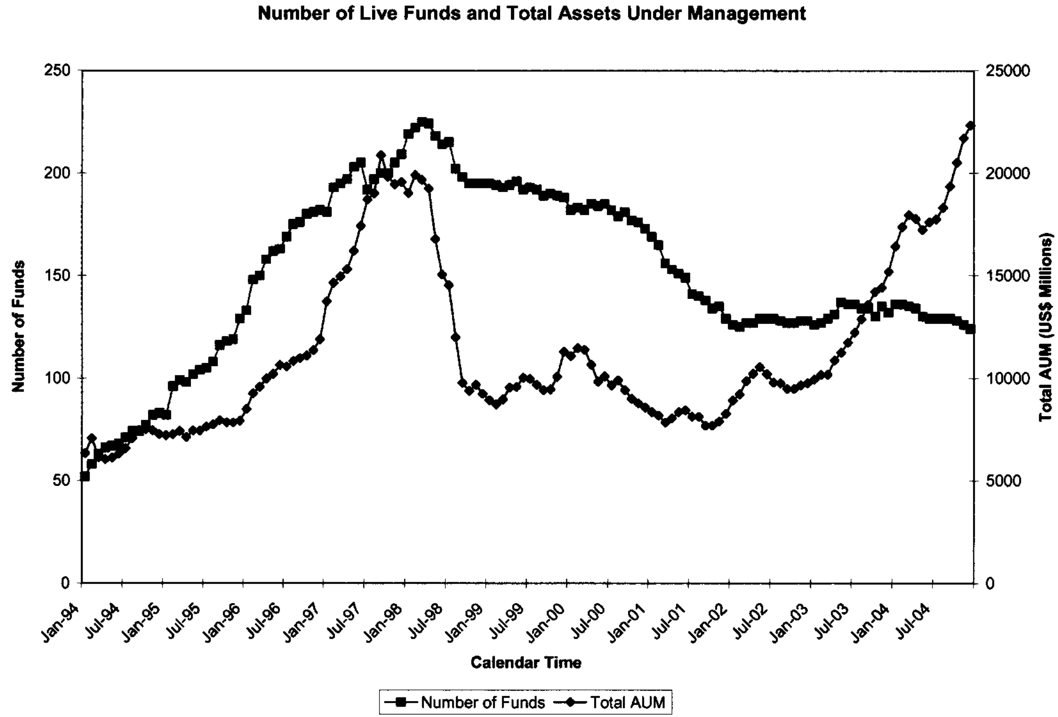


Figure 4: Alpha and Beta Funds

The figure plots the cumulative risk-adjusted equally-weighted return indices of two portfolios: Alpha and Beta funds. The funds are classified in the two categories by regressing the return on the modified Fung and Hsieh (2004b) model and sorting depending on the t-statistics of the intercept. The portfolio is then held for twelve months before being re-grouped. The data begin in April 1996 and end in December 2004.

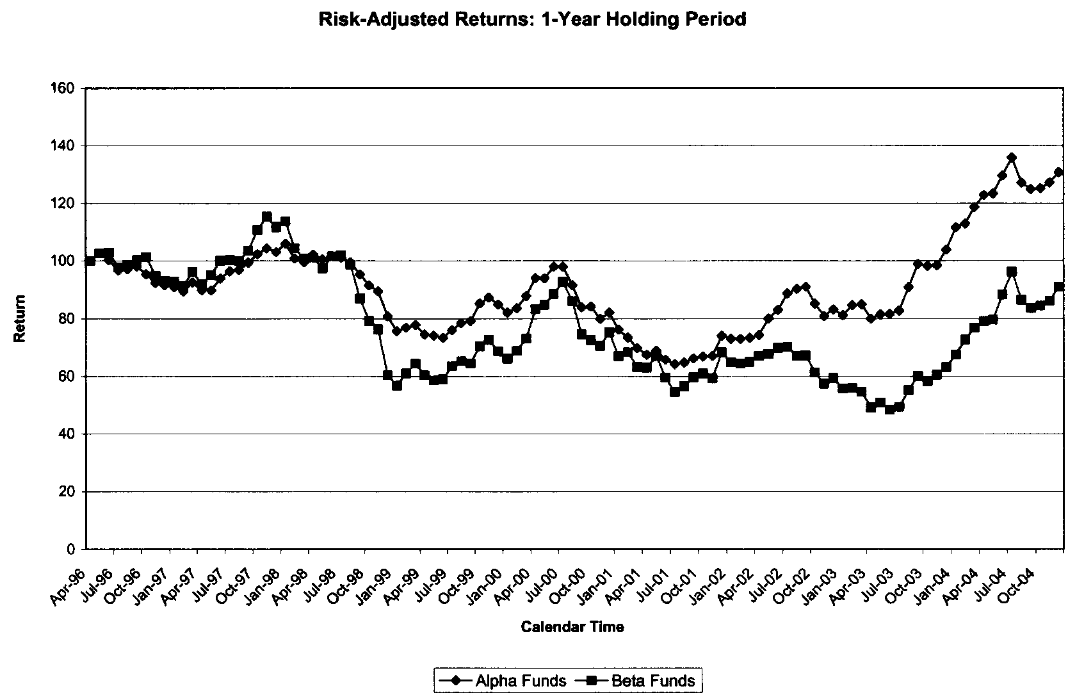
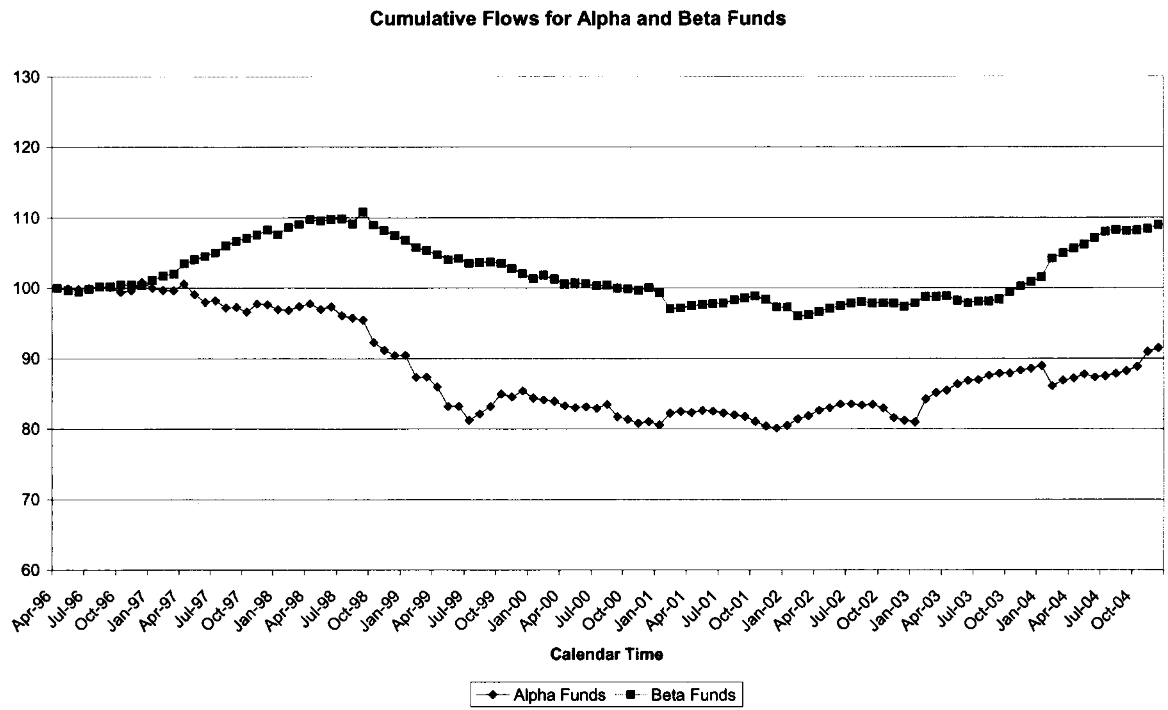


Figure 5: Cumulative Flows for Alpha and Beta Funds

The figure plots the cumulative equally-weighted capital flows for the two portfolios of Alpha and Beta funds. The data begin in April 1996 and end in December 2004. The funds are classified in the two categories by regressing the return on the modified Fung and Hsieh (2004) model and sorting depending on the t-statistics of the intercept. The portfolio is then held for twelve months before being re-grouped.



Chapter 2

Investments in Emerging Market Funds: An Extension

Maria Strömqvist*

Abstract

This paper examines three hypotheses, all related to investments in emerging markets. Previous research on emerging market hedge funds has shown that they have performed poorly in the past. Thus, the main objective of this paper is to investigate how an investor in emerging market hedge funds can achieve higher returns. More specifically, the following questions are asked: Can a subgroup of emerging market hedge funds be identified that performs better than the strategy on average? How can investors separate between hedge funds with true alpha generating skills and more opportunistic hedge funds in the emerging market strategy? And, finally, how does the performance of hedge funds compare to the performance of mutual funds in emerging markets?

Keywords: *Hedge funds; alpha; factor models; emerging markets; performance persistence; mutual funds*

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1 Introduction

This paper examines three hypotheses, all related to investments in emerging markets. Previous research has found that emerging market hedge funds have performed poorly in the past, both in absolute terms and relative to other hedge fund strategies. The main objective of this paper is to investigate how investors in emerging market hedge funds can achieve higher returns. More specifically, the following questions are asked: Can a subgroup of emerging market hedge funds be identified that on average performs better than the strategy? How can investors separate between hedge funds with true alpha generating skills (Alpha funds) and opportunistic hedge funds (Beta funds) in the emerging market strategy? And, finally, how does the performance of hedge funds compare to the performance of mutual funds in emerging markets?

The first section of this paper addresses the question of whether hedge fund managers with a regionally concentrated portfolio perform better than managers with a geographically diversified portfolio. Information is not as easily available in emerging markets as in developed markets. Thus, a more focused strategy might have some advantages over a global strategy. Previous literature on financial expertise has found investment ability to be more evident among managers that hold concentrated portfolios. Hence, investors might be able to increase their return on investment by selecting specialized funds instead of global funds.

The dataset of emerging market hedge funds is divided into funds with a global strategy and funds specializing in a specific geographic region. The findings show that specialized funds outperform global funds, but only in the latter part of the sample period. Between April 2000 and December 2004, specialist funds on average have a 4.20 percent higher risk-adjusted return per year than global funds. The discrepancy is of economic significance, considering that specialized funds then have almost twice as high a risk-adjusted return as global funds. However, sorting the specialist funds into three groups depending on focus area reveals that the high performance mainly stems from Latin American and Asian funds. Eastern European funds have not had a statistically significant alpha in any period.

The second section of the paper investigates the possibility of identifying hedge funds with skillful managers by looking at the market conditions when funds enter the sample. The assumption is that good market conditions attract a considerable amount of managers, especially less talented managers who will not have any persistence in risk-adjusted return. Thus, a fund that enters during down-market conditions and generates alpha should on average have a more skillful manager than a fund that enters and generates alpha during up-market conditions. The results indicate that the probability of a new fund with alpha being a "true" alpha generating fund is higher in bear markets than in bull markets. Thus, these findings can help investors increase their ability to separate between skill-based funds and more opportunitic funds in emerging markets.

The last section of the paper compares the performance of hedge funds and mutual funds that invest in emerging markets. Strömqvist (2007) finds hedge funds to be liquidity constrained in emerging markets and accordingly, they cannot fully take advantage of their freedom in investment strategies. Thus, hedge funds will not have a significant advantage over mutual funds when investing in emerging markets. Given that hedge funds charge much higher fees than mutual funds, it is reasonable to assume that mutual funds perform as well as hedge funds after fees. However, when comparing the return of hedge funds and mutual funds after fees in emerging markets, hedge funds still outperform mutual funds. One reason for this could be that skillful managers more often choose to manage hedge funds than mutual funds because of the beneficial compensation structure employed in hedge funds.

The rest of the paper is organized as follows. The next section presents related literature. Section 3 describes and motivates the research questions and hypotheses. Section 4 gives a description of the data and methodologies used. The results are presented in section 5 and the last section concludes the paper.

2 Related Literature

This paper is related to several strands of literature. At a general level, it relates to the literature on investments in emerging markets. More specifically, the performance of hedge funds and mutual funds. Finally, the paper also relates to the literature on financial expertise.

There are several papers that conclude that hedge funds have a positive risk-adjusted return (see, for example, Liang (1999), Fung and Hsieh (2004*a*) and Kosowski, Naik and Teo (2007)). Fung, Hsieh, Naik and Ramadorai (2007) perform the analysis on fund-of-hedge funds over a sample period from 1995 to 2004. They divide the sample period into three distinct sub-periods and find that it is mainly in the period September 1998 to March 2000 that the fund-of-hedge funds on average generate alpha. However, Strömqvist (2007) investigates the performance of emerging market hedge funds using similar periods as those employed in Fung et al. (2007). She finds that this particular strategy only adds value in the period after the high-tech bubble (April 2000 to December 2004).

Concerning the performance of hedge funds in different market conditions, Chen and Liang (2007) analyze the performance of hedge funds with a market timing strategy. They find that market timing hedge funds are better at timing the market in bear markets. Agarwal and Naik (2004) find that hedge fund indices show no correlation with the equity market index in up-market conditions, but a positive correlation in down-market conditions. They conclude that hedge funds offer greater diversification benefits in up-markets than in down-markets.

The performance of mutual funds in general is analyzed in Carhart (1997), which concludes that there is no persistence in performance and that any risk-adjusted returns can be explained by traditional risk factors and the momentum factor. Other papers showing that mutual fund managers do not add any value are Jensen (1968), Malkiel (1995) and Chen, Jegadeesh and Wermers (2000). Although many papers on mutual funds do not find any evidence of risk-adjusted returns, there are exceptions. One example is Bams and Otten (2002) which finds that European small-cap funds exhibit positive post-fee alpha.

On the subject of investments in emerging markets, Kaminsky, Lyons and Schmukler (2004) show that momentum trading, which is captured by the momentum factor suggested in Carhart (1997), is common among emerging market mutual funds. Moreover, Bekaert and Harvey (2003) analyze the performance of actual portfolio investments by U.S. investors using data on accumulated capital flows. They present evidence that the emerging market portfolios of U.S. investors outperform relevant benchmarks in total returns.

One paper that contrasts the performance of hedge funds to that of mutual funds is Liang (1999). In this paper, he compares efficient frontiers and Sharpe ratios of hedge fund and mutual fund strategies over the period 1992 to 1996. The findings show that the efficient frontier of hedge funds lies above the efficient frontier of mutual funds for all feasible standard deviations. Moreover, hedge funds on average have a higher Sharpe ratio as compared to mutual funds. Liang (1999) argues that because of the more flexible investment strategies, hedge funds are more likely to outperform mutual funds. However, Strömqvist (2007) finds evidence of hedge funds being constrained by limited liquidity in emerging markets and hence, they cannot fully take advantage of their freedom in investment strategies.

Agarwal, Boyson and Naik (2008) compare the returns of hedged mutual funds depending on the manager's previous experience. The authors conclude that hedged mutual funds managed by hedge fund managers perform better than hedged mutual funds managed by mutual fund managers.

Regarding the literature on financial expertise, Ericsson, Andersson and Cokely (2005) conclude that successful financial experts have a high degree of specialization. Kacperczyk, Sialm and Zheng (2004) test the hypothesis that U.S. mutual fund managers may decide to deviate from the standard diversified portfolio and concentrate their holdings in industries where they have informational advantages. They conclude that investment ability is more evident among managers that hold portfolios that are concentrated to a few industries. A related paper by Nanda, Wang and Zheng (2004) analyzes the performance of mutual fund families depending on how focused their investment strategies are across funds. They find evidence of a higher degree of concentration in strategies being positively related to performance for mutual fund families.

3 Research Questions and Hypotheses

The first section of the paper addresses the question of whether hedge fund managers with a regionally concentrated portfolio perform better than managers with a geographically diversified portfolio. Basic finance theory suggests that investors should diversify their holdings across markets to reduce the non-systematic risk of their portfolios (see Bodie, Kane and Marcus (2005)). Fund managers, however, might want to hold concentrated portfolios if they believe that this will generate superior returns. One example is the findings in Kacperczyk et al. (2004) where fund managers with more concentrated portfolios (in terms of industry) outperform more diversified funds. This can be applied to emerging market hedge funds, where some funds choose to be less diversified in terms of geographic region.[1] Thus, the first hypothesis in the paper is the following:

Hypothesis 1: *Hedge funds specializing in a specific geographic region outperform funds with a global strategy.*

Two counter-arguments can be made. First, given that global funds are more diversified, their risk-adjusted return may be superior to that of specialized funds. Second, consistent with Grinblatt and Keloharju (2000), if global funds have more resources to spend on research and more experienced managers, this will increase their performance relative to specialized funds.

The second section of the paper investigates the possibility of identifying the funds of skillful hedge fund managers by looking at the market conditions when funds enter the sample. Unlike the results in Fung et al. (2007) regarding fund-of-hedge funds, Strömqvist (2007) finds that investors cannot separate between good and bad funds in terms of alpha for emerging market hedge funds. Hence, to increase the ability of investors to identify good hedge funds in emerging markets, the idea is to take advantage of information from the timing of entering funds. The assumption is that good market conditions attract a large amount of managers, especially less

[1] There is no separation between funds that have a local headquarter and funds that do not. This question is analyzed in Teo (2006) for Asian hedge funds and in Coval and Moskowitz (2001) for mutual funds.

talented managers who will not have persistence in risk-adjusted return. Thus, a fund that enters during down-market conditions and generates alpha should on average have a more skillful manager than a fund that enters and generates alpha during up-market conditions. In Strömqvist (2007), a high share of funds with alpha in the crisis period between mid 1997 and the end of 1998 also had alpha in the next period (50 percent which was twice the average over the period 1994 to 2004). Thus, the following hypothesis is tested:

Hypothesis 2: *Hedge funds that enter in bear markets and have a positive alpha have a higher probability of having persistence in risk-adjusted returns than funds entering and performing well in bull markets.*

The last section of the paper compares the performance of mutual funds and hedge funds in emerging markets. Liang (1999) argues that given that hedge funds have more flexible investment strategies, they are more likely to outperform mutual funds. However, Strömqvist (2007) concludes that hedge funds are constrained by the limited liquidity in emerging markets. Chuhan (1992) argues that poor liquidity is one of the main reasons why foreign institutional investors are prevented from investing in emerging markets. If the limited liquidity prevents hedge funds from taking advantage of their flexibility in investment strategies, they will not have any significant advantage over mutual funds when investing in emerging markets. For example, Bris, Goetzmann and Zhu (2007) show that short-selling is prohibited or non-existing in most emerging markets. Thus, given that hedge funds charge much higher fees than mutual funds, it is reasonable to assume that emerging market mutual funds perform at least as well as hedge funds after deducting fees. Hence, the last hypothesis tested is the following:

Hypothesis 3: *Mutual funds perform as well as hedge funds (after fees) in emerging markets.*

4 Data and Methodologies

Both hedge fund and mutual fund data are used for the analysis. The hedge fund data are the same as in Strömqvist (2007), while the mutual fund data are collected from the CRSP Mutual Fund Database. Both datasets include dead funds to reduce the survivorship bias. The monthly data begin in January 1994 and end in December 2004. To be included, a fund is required to have at least 12 months of data and report assets under management. In total, the dataset consists of 418 emerging market hedge funds and 275 emerging market mutual funds. All returns are net-of-fees.

There are several differences between the hedge fund and the mutual fund datasets. One difference is that the hedge fund data are based on voluntary reporting, unlike the mandatory reporting for mutual funds. Another difference is that the hedge fund data are collected from four hedge fund databases, while the mutual fund data are only from one database. Thus, the selection bias is potentially greater in the mutual fund dataset than in the hedge fund dataset. The set of mutual funds is compared to the set of hedge funds in Panel A in Table V. The average emerging market mutual fund has a slightly longer life and is larger than the average emerging market hedge fund.

The analysis is performed both at a strategy level and a fund level. The strategy level analysis is performed using AUM-weighted return indices, calculated as in Strömqvist (2007). To derive the risk-adjusted return, the Fung and Hsieh (2004*b*) model is used. The factors are modified to fit the emerging market setting as in Strömqvist (2007). Hence, the equity factor is the MSCI Emerging Market Index and the bond index is the J.P. Morgan Emerging Markets Bond Index. Other factors are a small minus big equity factor and a credit risk factor. Moreover, the model contains three portfolios of lookback straddle options on currencies, commodities and bonds, which are supposed to capture the nonlinearity in hedge fund returns. The seven-factor model is used when the analysis is performed on hedge funds only. However, only four factors, excluding the non-linear option factors, are used for the comparison between hedge funds and mutual funds.[2]

The regression analysis is also performed separately on two sub-periods. Strömqvist (2007) performs the analysis on three sub-periods, but the break between the first and the second period is not significant for emerging market funds according to the Chow (1960) test. Thus, only two periods are used in this paper. The first period is January 1994 to March 2000, the

[2]The results are not altered if the option factors are included in the factor model.

peak of the high-tech bubble. The second period is April 2000 to December 2004.

For emerging market hedge funds, the dataset contains information regarding in which geographic markets a fund invests. This information is not available for mutual funds.[3] Hence, the first separation that can be made for emerging market hedge funds is that of global funds and funds specializing in a specific market. Second, the specialist funds can be divided into three groups: funds investing in Asia, Eastern Europe and Latin America. The majority of the emerging market hedge funds in the sample (64 percent) have a global strategy. Funds investing in Asia constitute the second largest group with 16 percent, followed by Eastern European funds (11 percent) and, finally, Latin American funds (9 percent). Global funds on average tend to be larger than specialized funds (see Panel A in Table I). Funds focusing on Latin America have the shortest average life, 3.1 years.

5 Results

5.1 Do Specialists Outperform Generalists?

This section presents the results from evaluating the performance of global and specialized funds. Basic finance theory suggests that investors should diversify their holdings across markets to reduce the non-systematic risk of their portfolios. However, fund managers might want to hold concentrated portfolios if they believe that some markets will outperform the overall market or if they have a superior ability to select profitable investment opportunities in a specific market.

To give some overview of the size of the different emerging market strategies, Table II presents the geographical distribution of assets under management over time. The columns display the percentage of total strategy AUM allocated to each focus area at the end of the year. The largest group of funds is global funds with, on average, 68 percent of the assets under management. Among the specialized strategies, funds focusing on Latin America have grown from managing practically no share of the assets under management to 13 percent in 2004. The opposite pattern can be seen for

[3]The only emerging market classification in the mutual fund dataset is "emerging market global".

funds focusing on Eastern Europe; the share has gone from 14 percent in 1994 to only two percent in 2004. Asian funds have had about 15 percent of the assets under management during the period.

As a preliminary analysis, Panel B in Table I gives the summary statistics for the average monthly value-weighted returns (above the risk free rate) for global and specialist funds, respectively, during 1994 to 2004. The mean return is lower for global funds, 0.44 percent compared to 0.59 percent, but the difference in total return is not statistically significant. Moreover, the volatility for specialized funds is higher, which can also be seen from the maximum and minimum returns in Table I. Latin American funds have the highest returns but also the highest volatility. The minimum returns occur in August 1998. This was a period of turbulence with the Asian and Russian crises as well as the collapse of Long-Term Capital Management. In this month, the funds focusing on Latin America lost more than one third of their value.

However, because hedge funds do not use relative benchmarks, it is more relevant to evaluate their performance using risk-adjusted returns. To test Hypothesis 1, risk-adjusted returns are calculated as the intercept when running a regression of value-weighted hedge fund index returns on the modified seven-factor model of Fung and Hsieh (2004*b*).

The results from the factor regressions can be found in Table III. Panel A shows the result from regressing the difference in value-weighted index returns between specialist and generalist funds on the risk factors. Hence, a positive intercept or coefficient indicates a higher value for specialist funds. Table III reveals that specialist funds have a higher alpha in all periods, which is consistent with Hypothesis 1. However, the alpha is only statistically significant in the second period, which is the post-bubble period from April 2000 to December 2004. In this period, specialists have a 35 basis points higher risk-adjusted return per month or 4.20 percent per year than global funds. The discrepancy is of economic significance considering that specialized funds then have almost twice as high a risk-adjusted return as global funds (see Panel B in Table III).

Panel B in Table III reveals that the high performance of specialist funds in the second period mainly stems from Latin American and Asian funds.

Eastern European funds have not had a statistically significant alpha in any period. In this context, it is interesting that Eastern European funds have the highest average fee (16.7 percent) and Latin American funds the lowest (15.3 percent) among the specialized strategies (see Table I). Hence, investors in Eastern European funds are paying a higher fee for lower performance than investors in Latin American funds.

As regards factor loadings, all funds have a large loading on emerging market equity. Global funds tend to have a larger loading on bonds than specialist funds. They also show some exposure to the option factor on bonds. Factor loadings tend to be largely the same for all specialized funds, but it is mainly funds focusing on Eastern Europe that are exposed to small cap equity and the option factor on commodities.

Figure 1 plots the cumulative risk-adjusted return for the two main strategies over the sample period. The figure confirms the results from the factor regressions; specialized funds only outperform global funds in the latter part of the sample period.

Malkiel (2003) claims that the most direct and convincing test of market efficiency is the test of the ability of professional fund managers to outperform the market. The fact that there are positive and statistically significant risk-adjusted returns in the latter part of the sample period is unlikely to be a sign of emerging markets becoming less efficient. Instead, it is more plausible that the liquidity in these markets has been too low for hedge funds to be able to take advantage of the inefficiencies. When liquidity has improved over time, so has the return of hedge funds. The positive risk-adjusted returns confirm the results in recent papers (see, for example, Kosowski et al. (2007)) that hedge fund managers are able to generate value from active management.

5.2 Identifying Alpha Funds

This section presents the results from investigating the possibility of identifying funds with skillful hedge fund managers. The analysis takes advantage of the information from the timing of entering funds and the market conditions in which they enter. The general idea is that good market conditions attract a large amount of managers, especially less talented managers who will not have any persistence in risk-adjusted return. Thus, a fund that enters the dataset during down-market conditions and generates alpha should on average have a more skillful manager than a fund that enters and manages to generate alpha during up-market conditions.

Bull and bear markets are classified using the value of the MSCI Emerging Market Index.[4] The periods are classified as follows:

1996:01	–	1997:07	Bull market
1997:08	–	1998:08	Bear market
1998:09	–	2000:03	Bull market
2000:04	–	2002:09	Bear market
2002:10	–	2004:12	Bull market

The first period contains the bullish market up until the start of the Asian crisis, which is then contained in the second period. The MSCI Emerging Market Index reached its bottom in August 1998. The period after the Asian crisis includes the high-tech bubble until March 2003, when the index peaked. It is followed by a bearish period until September 2002, including the Argentine default on its sovereign debt. The last period contains a positive market trend up to the end of the sample period in December 2004.

The analysis is performed following the methodology in Fung et al. (2007). The alpha is estimated as the intercept from running the modified Fung and Hsieh (2004*b*) model for each fund separately over the period in question. Hence, only funds with monthly returns throughout the specific period are used. The funds are then classified as Alpha or Beta funds using the t-statistic of the intercept. To make the analysis more robust, the t-statistics are cross-sectionally bootstrapped as in Fung et al. (2007).

Table IV displays the classification of entering funds. The averages for the funds that entered during up- and down-markets, respectively, are quite different. No funds that entered during a bull market and had alpha in that period also had alpha in the following period. For funds with alpha that entered during less favorable conditions, on average, more than half also

[4]The periods would not differ to any considerable extent if local indices were used, given that the correlations between the local emerging market indices and the global emerging market index are high. For example, all indices reach their lowest value in August 1998 and peak in March 2000.

had alpha in the consecutive period. Looking at the individual periods, in the crisis period between 1997 and 1998, 75 percent of the funds classified as having alpha also had alpha in the following period. In the bearish period after the high-tech bubble, 38 percent managed to keep adding value in the next period. Moreover, the probability for an alpha fund of only living one period is higher for bull market funds; 29 percent as compared to six percent for bear market funds.

Although the results are only based on evidence from two bull and bear markets, respectively, they indicate that the probability of a new fund with alpha being a "true" alpha generating fund is higher in bear markets than in bull markets[5]. This is consistent with the hypothesis that many less skilled managers enter the market in good times. There is no significant difference between entering funds that do not have alpha (Beta funds) that depend on market conditions.

5.3 Comparing the Performance of Mutual Funds and Hedge Funds in Emerging Markets

This section presents the result from comparing the performance of emerging market hedge funds to the performance of mutual funds investing in emerging markets. If the limited liquidity prevents hedge funds from taking advantage of their flexibility in investment strategies, they will not have any significant advantage over mutual funds when investing in emerging markets.

As a first analysis, the summary statistics in Panel B in Table V show that hedge funds have a higher average monthly return than mutual funds. The difference is even greater in medians. The differences are statistically significant. It is surprising that mutual funds have a higher volatility in returns at the strategy level, with a lower minimum and maximum than hedge funds. Liang (1999) argues that hedge fund returns should be more volatile than mutual fund returns because of the use of leverage, derivatives and short-selling. However, hedge funds being constrained from using these instruments may partly explain why they do not have a higher standard deviation in returns than mutual funds.

[5]There are no significant differences in results between funds with different geographic focus areas.

All returns are measured net-of-fees. Panel A in Table V displays the average fees of hedge funds and mutual funds. The fee structures of the two investment vehicles are very different. Typical for hedge funds is the high performance fee, which in this sample is on average almost 18 percent of the positive return in a given period. The performance fee for hedge funds does not have to increase and decrease symmetrically (as for mutual funds), which gives the compensation an option-like feature. The average performance fee for the mutual funds in the sample is 0.9 percent. A commonly quoted measure for fees in mutual funds is the expense ratio. This is the percentage of total investment that shareholders pay annually for mutual fund management fees and operating expenses. Emerging market mutual funds have an average expense ratio of two percent.

Figure 2 plots the cumulative total value-weighted index returns for emerging market hedge funds and mutual funds. The graph for hedge funds is above the graph for mutual funds most of the time, but it is mainly in the latter part of the sample period that hedge funds outperform mutual funds. Given that hedge funds charge much higher fees, the difference between the two graphs would be even greater if the returns included fees.

A second analysis looks at the risk-adjusted performance at the strategy level. Table VI displays the results from regressing the four linear Fung and Hsieh (2004*b*) factors on the difference in returns between hedge funds and mutual funds. Hence, a positive intercept or coefficient indicates a higher value for hedge funds. The alpha for the overall period is small and not statistically different from zero. However, the alpha is negative (although not statistically significant) in the first period, indicating that mutual funds had a better performance than hedge funds between 1994 and March 2000. And the alpha is positive and statistically significant in the second period when hedge funds outperformed mutual funds. In general, hedge funds have had a lower exposure to equity than mutual funds.

Figure 3 shows the cumulative risk-adjusted return at the strategy level over the sample period for hedge funds and mutual funds. Both categories have performed poorly in absolute terms over time, with graphs below the starting value of 100 throughout the period. However, hedge funds have performed slightly better, which should also be seen in the light of the performance being calculated on net-of-fee returns. Although the two graphs follow each other quite closely over time, the gap widens somewhat in the latter part of the sample period.

Table VII shows the results at the fund level. In this analysis, the return series of each fund is regressed on the four factors and the table then displays summary statistics regarding the alpha and R-square for the sample of hedge funds and mutual funds and the difference between the two. The mean fund alpha for hedge funds is twice as high as for mutual funds (0.4 compared to 0.2). The difference in medians is even greater and also statistically significant at the 5%-level using a Wilcoxon Mann-Whitney test. However, the dispersion in performance between funds is much higher for hedge funds. Moreover, a higher proportion of hedge funds have a positive alpha (23 percent) than mutual funds (13 percent). As expected, the fit of the regression model is better for mutual funds than for hedge funds, which is consistent with the findings in Fung and Hsieh (1997).

Strömqvist (2007) found that there was some weak persistence in the risk-adjusted performance for emerging market hedge funds, especially in the latter part of the sample period. The question is if this is also true for emerging market mutual funds. The analysis is performed following the methodology in Fung et al. (2007). The alpha is estimated as the intercept from running the modified four factor Fung and Hsieh (2004*b*) model over 18 months of data for each fund separately. Hence, only funds with monthly returns throughout the entire period in question are used. The funds are then classified as Alpha or Beta funds using the t-statistic of the intercept. The t-statistics are cross-sectionally bootstrapped as in Fung et al. (2007). Moreover, the same periods as in Strömqvist (2007) are used to make the results for mutual funds more comparable to those for hedge funds.[6]

The results from the transition probability analysis for mutual funds are shown in Table VIII. Panel A shows the transition probabilities for mutual funds in seven different periods. Panel B in the same table shows the average transition probabilities and also includes the results regarding hedge funds from Strömqvist (2007) for comparison. Although mutual funds have a slightly higher share of funds with alpha (16 percent compared to 11 percent), there is no persistence in risk-adjusted returns. For mutual funds,

[6]Although the analysis on hedge funds is performed using the seven-factor model, the results do not change quantitatively if only four factors are used.

Alpha funds actually have a lower probability than Beta funds of generating alpha in the next period. For hedge funds, the result is clearly the opposite, indicating persistence in returns.

One reason for the result that hedge funds outperform mutual funds could be that skillful managers more often choose to manage hedge funds than mutual funds, due to the beneficial compensation structures. Support for this is given in Agarwal et al. (2008) where the authors conclude that hedged mutual funds managed by hedge fund managers perform better than hedge mutual funds managed by mutual fund managers.

6 Conclusions

This paper investigates three questions related to investments in emerging markets. The results in Strömqvist (2007) show that the emerging market hedge funds have had a poor performance on average. Thus, the main objective of this paper is to investigate how an investor in emerging market hedge funds can achieve higher returns. The paper delivers three results regarding this question.

First, investors are better off investing in hedge funds with a regionally concentrated portfolio than in funds with a geographically diversified portfolio. The higher performance of specialist funds is economically significant in the latter part of the sample period; 4.2 percent per year in risk-adjusted returns.

Second, using the time of entry and performance in that period as indicators, investors can increase their ability to separate true alpha generating funds from more opportunistic funds. The findings show that the probability of a new fund with alpha being a true alpha generating fund is higher in bear markets than in bull markets.

And finally, despite hedge funds charging much higher fees than mutual funds and despite the constraints the limited liquidity sets on investment flexibility, hedge funds still outperform mutual funds after fees in emerging markets. Hence, if investors want to allocate part of the portfolio to emerging markets, hedge funds are still a better alternative than mutual funds.

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Table I
Summary Statistics Hedge Fund Strategies

This table presents summary statistics for emerging market hedge funds sorted into different strategies. The first section shows summary statistics for funds with a global strategy (generalists) and funds that only invest in a specific market (specialists). In the second section of the table, specialist funds are divided into Asian, Eastern European and Latin American funds. The first panel displays, in rows, the number of funds in the sample, the average life in years, average fund assets under management (AUM), average performance fee or expense ratio. The second panel shows summary statistics for the monthly value-weighted returns (in excess over the three-month U.S. Treasury bill).

	Generalists	Specialists	Asia	Eastern Europe	Latin America
Panel A: Summary Statistics Sample					
Number of funds	271	147	66	47	34
Average life in years	4.5	4.1	4.3	4.6	3.1
Average AUM (US $MN)	79.4	70.6	76.6	47.5	90.9
Average performance fee (%)	18.6	15.9	15.7	16.7	15.3
Funds with lockups (%)	10	14	9	26	5
Panel B: Excess returns value-weighted indices (%)					
Mean	0.44	0.59	0.56	0.54	0.67
Median	0.81	1.30	1.05	0.89	1.22
Standard deviation	4.32	5.79	6.13	5.72	6.21
Minimum	-18.75	-28.66	-29.25	-24.47	-34.91
Maximum	12.92	20.00	21.06	18.92	17.05

Table II
Emerging Market Hedge Funds:
Geographical Distribution of Assets under Management

This table presents the geographical distribution of assets under management (AUM) over time for emerging market hedge funds. The funds are sorted into four focus areas; Asia, Eastern Europe, Latin America and Global. The columns display the percentage of total strategy AUM that is allocated in each focus market at the end of the year, in rows.

	Distribution across Focus Markets			
Year	**Asia**	**Eastern Europe**	**Latin America**	**Global**
1994	14%	14%	0%	72%
1995	13%	11%	0%	76%
1996	14%	12%	6%	68%
1997	19%	11%	6%	64%
1998	21%	8%	5%	66%
1999	17%	9%	7%	67%
2000	15%	7%	6%	72%
2001	18%	5%	13%	64%
2002	18%	3%	13%	66%
2003	17%	3%	12%	68%
2004	16%	2%	13%	68%

Table III
Factor Regressions

This table presents results from regressing monthly value-weighted strategy index returns for emerging market hedge funds on the Fung and Hsieh (2004b) factors, modified to fit the emerging market setting. The left hand-side variable in each regression is the AUM weighted (net-of fees) excess return. The seven factors used are excess return on the MSCI Emerging Market Index (MSCI EM); a small minus big (SMB) capitalization factor; three portfolios of lookback straddle options (PTFs) on bonds, commodities and foreign exchange; the spread of Moody's BAA corporate bond returns index over the U.S. 10 year maturity Treasury bond (BAA spread), and finally the J.P. Morgan Emerging Markets Bond Index (JPM). For each period represented in a row, the columns present the intercept (alpha), the slope coefficients on the factors and the adjusted R-square. The first period is January 1994 to March 2000, and the second period is April 2000 to December 2004. Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors are employed (6 lags). Significance at the one, five and ten percent level is given by ***, ** and * respectively. As indicated in rows, the regression is performed first on overall sample and then on the two sub-periods. Panel A displays the results using the difference in return between specialist and generalist funds. Panel B presents the results for the funds sorted into four focus areas; Global, Asia, Eastern Europe and Latin America.

Return	α	**MSCI EM**	**SMB**	**PTF Bonds**	**PTF Com**	**PTF FX**	**BAA Spread**	**JPM**	R^2
			Panel A: Hedge Fund Specialists versus Generalists						
Special -General									
Overall period	0.022	0.130 ***	0.105	0.006	0.023	-0.001	0.145	0.060	0.26
Period I	0.005	0.143**	0.098	0.014	0.025	-0.002	0.552**	0.071	0.23
Period II	0.350**	0.156	0.091	0.008	0.018	-0.008	-0.165	0.103	0.26
			Panel B: Hedge Funds divided into Focus Areas						
Global									
Overall period	0.389	0.537***	0.059	-0.029**	0.006	0.009	0.264	0.216***	0.77
Period I	0.215	0.531***	0.086	-0.021	0.001	0.016	0.707	0.155***	0.80
Period II	0.403**	0.462***	-0.017	-0.007	0.029**	0.006	0.124	0.219**	0.87
Asia									
Overall period	0.470	0.674***	0.147	-0.025	0.022	0.004	0.609	0.122	0.65
Period I	0.057	0.659***	0.189	-0.004	0.019	0.016	1.442*	0.229**	0.73
Period II	0.757*	0.616***	0.036	-0.002	0.047	-0.009	0.251	0.253	0.63
Eastern Europe									
Overall period	0.541	0.674***	0.181***	-0.034	0.083**	-0.006	0.050	0.157	0.68
Period I	0.589	0.660***	0.237***	-0.027	0.093*	-0.003	0.581	0.233	0.75
Period II	0.360	0.571***	0.079	-0.000	0.083***	0.003	0.012	0.324**	0.77
Latin America									
Overall period	0.703	0.726***	0.117	-0.022	0.011	0.032	0.209	0.014	0.67
Period I	0.158	0.830***	0.085	0.010	0.009	0.029**	1.835***	0.016	0.74
Period II	1.363***	0.589***	0.188*	-0.004	0.022	0.011	-0.334	0.110	0.68

Table IV
Transition Probabilities for Entering Hedge Funds

The rows show five bull and bear periods in which entering funds are classified as Alpha and Beta funds. The market conditions are determined using the value of the MSCI Emerging Market Index. A fund is classified as an entering fund if it is the first period in which the fund has 18 months of data. The classification into Alpha and Beta funds is made depending on the t-statistic of the intercept when running the modified Fung and Hsieh (2004b) model on the funds' return series. The t-statistics are bootstrapped cross-sectionally using the methodology in Fung et al. (2007). The columns are, in order: the total number of entering funds in each of the classification periods; the percentages of total classified as Alpha and Beta funds; the percentages within each classification group that are classified in the subsequent period as Alpha or Beta funds or which exited the sample. The second part of the table presents the average transition probabilities for Alpha and Beta funds in bull and bear markets and the difference between them.

Period	Dates	EM Market	Number of funds entering	Alpha	Beta	From/To:	Alpha	Beta	Exited
1	*1996:1-1997:7*	Bull	69	0.10	0.90	Alpha	0.00	0.43	0.57
						Beta	0.03	0.50	0.47
2	*1997:8-1998:8*	Bear	63	0.06	0.94	Alpha	0.75	0.25	0.00
						Beta	0.03	0.73	0.24
3	*1998:9-2000:3*	Bull	39	0.05	0.95	Alpha	0.00	1.00	0.00
						Beta	0.19	0.32	0.49
4	*2000:4-2002:9*	Bear	36	0.22	0.78	Alpha	0.38	0.50	0.13
						Beta	0.07	0.54	0.39
5	*2002:10-2004:12*	Bull	33	0.09	0.91				

Averages	From/To:	Alpha	Beta	Exited
	Alpha funds			
	Bull market	0.00	0.72	0.29
	Bear market	0.57	0.38	0.06
	Difference	-0.57	0.34	0.23
	Beta funds			
	Bull market	0.11	0.41	0.48
	Bear market	0.05	0.63	0.32
	Difference	0.06	-0.22	0.16

Table V
Hedge Funds versus Mutual Funds

This table presents summary statistics for hedge funds and mutual funds investing in emerging markets. The first panel displays, in rows, the number of funds in the sample, the average life in years, average fund AUM and fees. Panel B shows summary statistics for the monthly value-weighted returns (in excess over the three-month U.S. Treasury bill) for the two categories. The parameters given in rows are the mean, median, standard deviation, minimum and maximum. Significance at the one and five percent level is given by *** and ** respectively.

Panel A: Summary Statistics Sample	**Hedge Funds**	**Mutual Funds**	
Number of funds	418	275	
Average life in years	4.4	5.6	
Average AUM (US $MN)	75.6	102.2	
Average performance fee (%)	17.7	0.9	
Equally-weighted expense ratio (%)	-	2.0	
Panel B: Excess Returns Value-Weighted Indices (%)	**Hedge Funds**	**Mutual Funds**	**Difference**
Mean	0.48	0.31	0.17**
Median	1.18	0.88	0.30***
Standard deviation	4.73	5.83	-1.10
Minimum	-22.71	-26.33	
Maximum	15.04	14.76	

Table VI
Factor Regressions: Hedge Funds versus Mutual Funds

The table presents results from regressing the difference between monthly hedge fund and mutual fund strategy index returns on the four linear factors in the modified Fung and Hsieh (2004b) model (excluding the option factors). The left hand-side variable is the difference between the AUM weighted (net-of fees) excess return between hedge funds and mutual funds. The four factors used are excess return on the MSCI Emerging Market Index (MSCI EM); a small minus big (SMB) capitalization factor; the spread of Moody's BAA corporate bond returns index over the U.S. 10 year maturity Treasury bond (BAA spread), and finally the J.P. Morgan Emerging Markets Bond Index (JPM).

For each period represented in a row, the columns present the intercept (alpha), the slope coefficients on the factors and the adjusted R-square. Newey-West (1987) heteroskedasticity and autocorrelation consistent standard errors are employed (6 lags). Significance at the one, five and ten percent level is given by ***, ** and * respectively.

As indicated in rows, the regression is performed first on overall sample and then on the two sub-periods. The first period is January 1994 to March 2000, and the second period is April 2000 to December 2004.

Return	α	MSCI EM	SMB	BAA Spread	JPM	R^2
Hedge Funds – Mutual Funds						
Overall period	0.008	-0.272***	-0.060	0.149	0.131	0.412
Period I	-0.329	-0.233	-0.085	1.343***	0.090**	0.353
Period II	0.459***	-0.269***	-0.049	-0.142	0.542*	0.686

Table VII
Individual Fund Alpha: Hedge Funds versus Mutual Funds

The table displays the average fund alpha for hedge funds and mutual funds, respectively, when regressing the return of the individual funds on the modified Fung and Hsieh (2004b) four-factor model. The mean, median, standard deviation, percentage of funds with a positive or no alpha and the median R-square are given in rows. Significance at the one and five percent level is given by *** and ** respectively.

	Hedge Funds	**Mutual Funds**	**Difference**
Mean	0.412	0.191	0.22
Median	0.512	0.195	0.32**
Standard deviation	2.751	0.694	2.06***
% pos	22.6	13.1	9.50***
No alpha (%)	77.4	86.9	-9.50***
Median R-square	36.6	88.7	-52.1***

Table VIII
Transition Probabilities for Mutual Funds

Panel A shows the 18-month period in which funds are classified as Alpha and Beta *mutual* funds. The classification is made depending on the t-statistic of the intercept when running the modified Fung and Hsieh (2004b) model on the funds' return series. The t-statistics are bootstrapped cross-sectionally using the methodology in Fung et al. (2007). The columns are, in order: the total number of funds with 18 months of return history in each of the classification periods; the percentages of total classified as Alpha and Beta funds; the percentages within each classification group that are classified in the subsequent period as Alpha or Beta funds or which exited the sample. Panel B displays the average transition probabilities for mutual funds and hedge funds (hedge fund results from Strömqvist (2007)) and the difference between Alpha and Beta funds. A Wald test is used to test whether the transition probabilities differ between Alpha and Beta funds and significance at the one and five percent level is given by *** and ** respectively.

Panel A: Transition Probabilities Mutual Funds							
Period	**Number of funds**	**Alpha**	**Beta**	**From/To:**	**Alpha**	**Beta**	**Exited**
1994:7-1995:12	59	0.24	0.76	Alpha	0.07	0.93	0.00
				Beta	0.18	0.78	0.04
1996:1-1997:6	109	0.23	0.77	Alpha	0.08	0.92	0.00
				Beta	0.27	0.67	0.06
1997:7-1998:12	157	0.26	0.74	Alpha	0.02	0.90	0.07
				Beta	0.00	0.87	0.13
1999:1-2000:6	182	0.01	0.99	Alpha	0.00	1.00	0.00
				Beta	0.10	0.73	0.16
2000:7-2001:12	186	0.12	0.88	Alpha	0.04	0.91	0.04
				Beta	0.03	0.69	0.28
2002:1-2003:6	165	0.04	0.96	Alpha	0.17	0.83	0.00
				Beta	0.18	0.76	0.06
2003:7-2004:12	173	0.23	0.77				
Panel B: Average Transition Probabilities: Hedge Funds versus Mutual Funds							
		Alpha	**Beta**	**From/To:**	**Alpha**	**Beta**	**Exited**
Mutual Funds		0.16	0.84	Alpha	0.06	0.92	0.02
				Beta	0.13	0.75	0.12
				Difference			-
					-0.07**	0.17***	0.10***
Hedge Funds		0.11	0.89	Alpha	0.26	0.46	0.13
				Beta	0.07	0.67	0.26
				Difference			-
					0.19***	-0.21***	0.13***

Figure 1: Cumulative Risk-Adjusted Returns Hedge Funds: Generalists versus Specialists

The figure plots the cumulative non-systematic value-weighted excess return indices of hedge funds with a global strategy and funds focusing on a specific region. The non-systematic return is the intercept when running the modified Fung and Hsieh (2004) factor model. The data begin in April 1994 and end in December 2004.

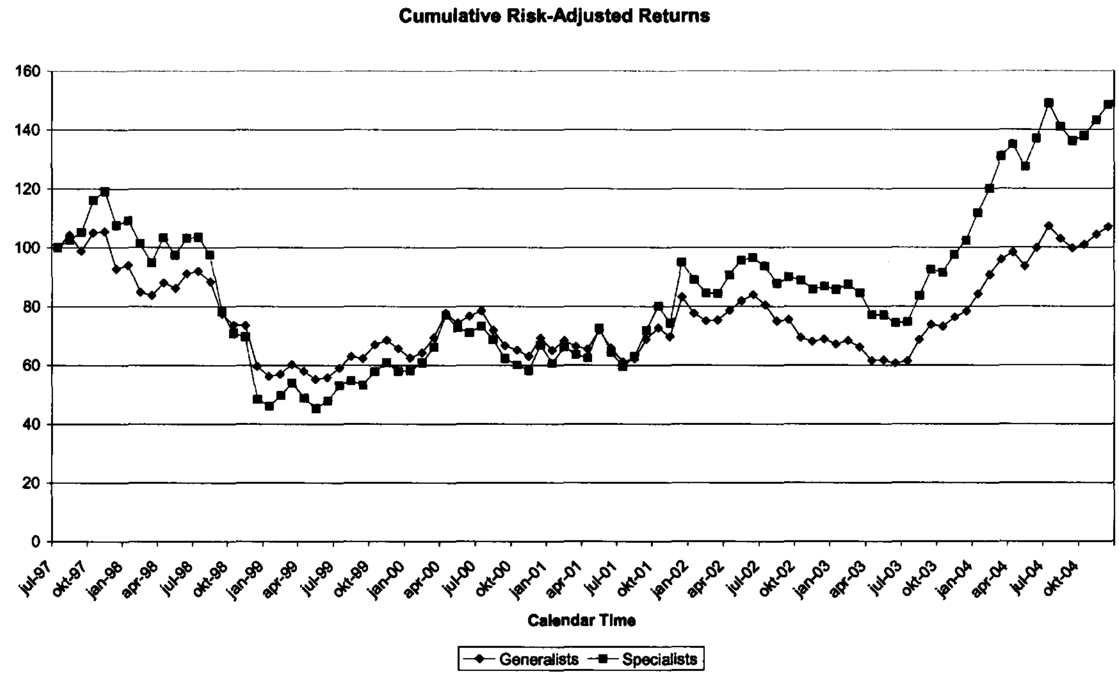


Figure 2: Cumulative Total Returns: Hedge Funds versus Mutual Funds

The figure plots the cumulative total value-weighted excess return indices of the emerging market strategy for hedge funds and mutual funds. The data begin in the first month of 1994 and end in the final month of 2004.

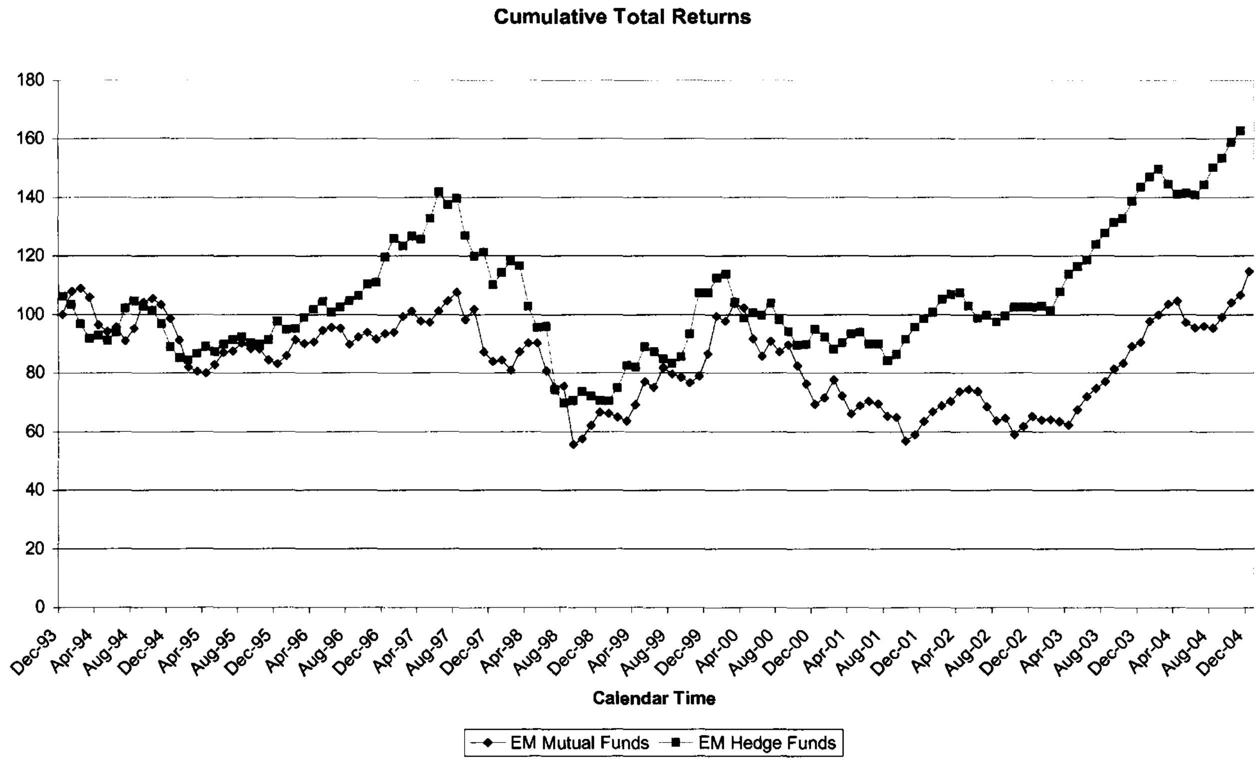
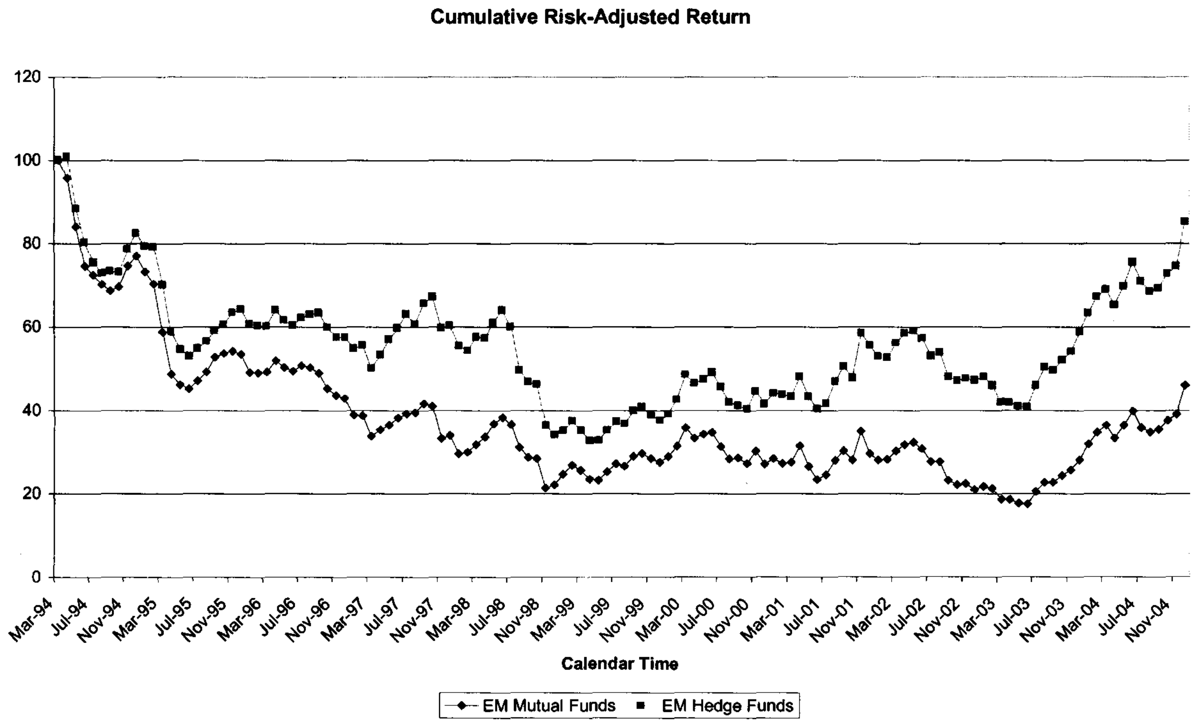


Figure 3: Cumulative Risk-Adjusted Returns: Hedge Funds versus Mutual Funds

The figure plots the cumulative risk-adjusted equally-weighted excess return indices of emerging market hedge funds and mutual funds. The data begin in April 1994 and end in December 2004.



Chapter 3

Capacity Constraints and Hedge Fund Strategy Returns*

Narayan Y. Naik†, Tarun Ramadorai‡ and Maria Strömqvist§

Abstract

Hedge funds have generated significant absolute returns (alpha) in the decade between 1995 and 2004. However, the level of alpha has declined substantially over this period. We investigate whether capacity constraints at the level of hedge fund strategies have been responsible for this decline. For four out of eight hedge fund strategies, capital inflows have statistically preceded negative movements in alpha, consistent with this hypothesis. We also find evidence that hedge fund fees have increased over the same period. Our results provide support for the Berk and Green (2004) rational model of active portfolio management.

Keywords: *Hedge funds; capacity constraints; alpha; factor models; performance fees; flows*

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absolute components. We regress the latter component on the lagged capital flows into each strategy (making sure to avoid any potential overlap). The analysis reveals that high capital flows precede statistically significant declines in alpha. However, there is interesting cross-sectional variation in these findings. Relative Value, Directional Traders, Emerging Markets and Fixed Income strategies appear to show evidence of capacity constraints, while there is little evidence that the other strategies are subject to capacity constraints.

Finally, we present evidence consistent with the second channel via which Berk and Green (2004) suggest alpha will be zero in equilibrium – a steady increase in incentive fees in the hedge fund industry, especially in the most recent period of time.

We conclude that capacity constraints are indeed a concern for seekers of alpha in a subset of hedge fund strategies. Although this is disappointing news for investors, it is good news for the analysis of Berk and Green (2004). These authors present a rational model of active management that predicts that in an economy with competitive provision of capital and rational investors, differential managerial ability will not be detectable by an econometrician. In particular, they show that under these assumptions alpha will be zero. Our results suggest that the mechanisms they put forward may provide a consistent rationale for the declining alpha we see in our hedge fund strategy return data.

The organization of the paper is as follows: section two describes our data, section three presents our methodology, section four discusses the results, and section five concludes.

2 Data

2.1 Hedge Fund Data

We use a large and comprehensive dataset of hedge funds. Our data are available for the period between January 1994 and December 2004. Our data (which include data on dead funds) are drawn from the union of four large databases namely HFR, TASS, CISDM (formerly ZCM/MAR), and MSCI. This enables us to resolve occasional discrepancies among different databases and to create a sample that is more representative of the entire hedge fund industry. Only funds that report assets under management (AUM) are included in the dataset. A careful filter is applied to the data. We first exclude funds-of-hedge-funds, and then eliminate any fund with flows greater (less) than 500 (100) percent of its prior month's AUM at any point in its history. This leaves us with a total of 7,610 funds.

The first panel of Table I shows the evolution of the aggregate AUM in the hedge fund industry. Figure 1 plots the final column of Panel 1, and confirms the many press reports about the dramatic growth of the hedge fund industry. Aggregate AUM in the industry has grown from U.S. $ 70 billion in 1994 to U.S. $ 740 billion in 2004.

Research by Fung and Hsieh (1997) and Brown and Goetzmann (2003) shows that there are five to eight distinct style factors in hedge fund returns. Following these insights, and the classification in Agarwal, Daniel and Naik (2005), we classify the reported hedge fund strategies into eight broad categories: Security Selection, which comprises long/short equity hedge, equity hedge and equity market neutral funds; Macro; Relative Value, which comprises merger arbitrage, convertible arbitrage and statistical arbitrage funds; Directional Traders, which includes vendor classifications such as sector, long bias and equity non-hedge; Multi-Process, which also contains event driven funds; Emerging Markets; Fixed Income, and Other, which is a catch-all category containing strategies such as managed futures and discretionary trading. The first panel in Table I also shows the time evolution of the share of total hedge fund AUM in each strategy. There has been interesting cross-sectional variation in this time evolution, with growth in Security Selection, Multi-Process and Relative Value funds at the expense of Macro funds, and to a certain extent, Emerging Markets funds.

The second panel in Table I enumerates the number of funds in each of the strategies in each year of our data. The table reveals that the strategies which have experienced growth in AUM have also seen an increase in the number of funds. In thinking about capacity constraints, we are often confronted with the possibility that high return generating funds could close to new money, thus preventing constraints on alpha generation from binding. Panel 2 suggests that there may be entry of new funds into alpha-generating sectors, regardless of whether successful funds close to new money.

2.1.1 Flows

We compute dollar flows F_{it} for fund i during month t as follows:

$$F_{it} = A_{it} - A_{it-1}(1 + r_{it}) \tag{1}$$

Here A_{it}, A_{it-1} and r_{it} are the AUM for fund i at the end of month t, and $t-1$, and the returns accrued from month $t-1$ to t respectively. Note that we assume that the flows came in at the end of the month, subsequent to the accrual of returns. We then compute strategy level flows by aggregating individual fund flows up to the level of strategies, and scale the dollar flows by strategy-aggregated end-of-previous-month AUM:

$$f_{st} = \left(\sum_{i=1}^{N_s} F_{it}\right) / \left(\sum_{i=1}^{N_s} A_{it-1}\right) \tag{2}$$

The third panel in Table I shows the share of flows that have gone into each strategy in each year. There is significant cross-sectional and time-series variation in flow shares. For example, in 1995, although aggregate flows into the industry only measured U.S. \$ 508 million, this disguises a large reallocation away from Macro funds and Emerging Markets funds and towards Relative Value funds.

2.1.2 Returns

We compute value-weighted excess return indices for each strategy. Value weighted excess returns are constructed as

$$r_{st}^{VW} = \sum_{i=1}^{N} \omega_{it}(r_{it} - r_{ft}) \tag{3}$$

where $\omega_{it} = A_{it-1}/(\sum_{i=1}^{N_s} A_{it-1})$ are AUM weights reconstructed each month, r_{it} is the (net-of-fee) return on fund i, a member of strategy s in month t, and r_{ft} is the return on the three-month U.S. Treasury bill in month

t, obtained from Datastream. Table II shows that the annualized value-weighted mean excess return lies between 2.8 and 8.4 percent depending on the strategy. The standard deviation of excess returns is also quite high, ranging between 2.6 and 16.4 percent on an annualized basis.

2.2 Factor Return Data

To calculate the systematic component of strategy index returns, we regress them on factors that have been shown to have explanatory power for hedge fund returns. These factors are drawn from the work of Fung and Hsieh (2004). They are: the excess return on the S&P 500 index (SNPMRF); a small minus big factor (SCMLC) constructed as the difference of the Wilshire small and large capitalization stock indices; three portfolios of lookback straddle options on currencies (PTFSFX), commodities (PTFSCOM) and bonds (PTFSBD), which are constructed to replicate the maximum possible return to a trend-following strategy on the underlying asset, all in excess returns; the yield spread of the U.S. ten-year Treasury bond over the three-month T-bill, adjusted for the duration of the ten-year bond (BD10RET) and the change in the credit spread of the Moody's BAA bond over the ten-year Treasury bond, also appropriately adjusted for duration (BAAMTSY).

3 Methodology

3.1 Risk-Adjusted Performance Evaluation

We first estimate regressions of hedge fund strategy returns on the seven-factor model. Writing r_{st} for the value-weighted return index for strategy s at time t, we estimate:

$$r_{st} = \alpha_s + X_t\beta_s + \varepsilon_{st} \tag{4}$$

where:

$$X_t = [SNPMRF_t \; SCMLC_t \; BD10RET_t \; BAAMTSY_t \\ PTFSBD_t \; PTFSFX_t \; PTFSCOM_t]$$

A static factor analysis of the risk structure of hedge fund strategy returns is not appropriate if managers change their alpha-generating tactics over time. Therefore, we estimate equation (4) separately for three sub-periods, thus allowing for breakpoints in the relationship between strategy returns and the seven factors. The breakpoints are the same as those employed in Fung et al. (2007), and correspond to the collapse of Long-Term Capital Management in September 1998, and the peak of the technology bubble in March 2000. Finally, the validity of these pre-specified breakpoints is checked using the Chow (1960) test for structural breaks.

3.2 Detecting Capacity Constraints

We begin with a simple analysis of the capital flows experienced by the different strategies over the three sub-periods identified in the previous section. If capacity constraints are responsible for movements in alpha, we expect that high flows would precede reductions in alpha. This intuition is formalized by conditioning movements in alpha on flows into the various hedge fund strategies.

To construct a measure of hedge fund strategy alpha, we decompose strategy returns into systematic and absolute return components. If we ran a single regression for each strategy, we would get a static decomposition of the strategy's returns using a stable set of parameters (alpha and loadings), which do not exhibit any time variation. However, our goal is to explain time variation in alpha. This time variation is captured by running a rolling factor regression each month using a 12-month estimation window.[3]

In our analysis, we employ two different factor models: the full set of seven Fung-Hsieh factors, and a subset of these factors, the four non-options factors in the set (all except the three PTF lookback straddle option factors) to check the robustness of our results. We estimate:

$$r_{sw} = \alpha_{sw} + X_w\beta_{sw} + \varepsilon_{sw} \tag{5}$$

Here, the w subscript represents the window over which the rolling regression is run. For example, the first such w represents the first 12 months of

[3]We also use a 24-month estimation window and the results remain the same.

the available data, January 1994 to December 1994, and the second return window is February 1994 to January 1995. r_{sw} is the vector of the 12 return observations for strategy s for window w, and X_{sw} the matrix of factors over the same window. The regressions result in a series of estimated factor loadings β_{sw} corresponding to each value of w.

With each set of estimated factor loadings, we construct an out-of-sample quantitative measure of hedge fund ability, $alpha\_u_{st}$. For example, $alpha\_u_{s,Jan1995}$ for January 1995 is constructed by subtracting the product of the factor loadings estimated over the January 1994 to December 1994 window and the factor realizations in January 1995 from the return observation for January 1995.

We regress $alpha\_u_{st}$ on lagged strategy-specific capital flows and three conditioning variables. We control for size and using the total AUM contained within the strategy (using a logarithmic scale), additionally conditioning on the squared size to control for potential non-linearity in the relationship. We also follow the methodology in Getmansky (2004), and control for the number of funds within a strategy in the prior year, as a proxy for competition between funds in the strategy.

Fung et al. (2007) find that there are three distinct periods between 1994 and 2004 that are of importance to hedge funds. We therefore estimate separate regressions for each one of these periods. Finally, in our regressions, we use flows from month $t-13$ to $t-24$ to explain $alpha\_u$ for period t, thereby ensuring that there is no overlap between our $alpha\_u$ measures and our flow measures. Our final specification is:

$$alpha\_u_{st} = \kappa_s + \phi(f_{st-13} + .. + f_{st-24}) + \upsilon AUM_{st-12} + \lambda AUM^2_{st-12} + \chi Number_{st-12} + \zeta_{st} \tag{6}$$

In equation (6), we interpret a negative value of ϕ as evidence of capacity constraints in the strategy.

We also look for confirming evidence of capacity constraints in time variation in the structure of fees in the hedge fund industry. In the Berk and

Green (2004) model, managers appropriate any remaining absolute return by raising their fees. As we cannot observe the fee structure each year for the funds in our data, we assume that the fee structure is the same for a fund throughout its life. We inspect the equal weighted average incentive fee and management fee for each year across all funds in each strategy.[4]

To get around the assumption that the fee structure for a fund remains the same throughout its life, we also employ another measure, the average fee across all funds born each year. If the fees reported in the database are only correct for the first year after a fund entered, and are not updated when changes occur, the data for funds born each year will provide a clearer picture.

3.3 A Note on Estimation

In our regressions, we use 12 monthly lags of flows.[5] There are lock-ups and other restrictions associated with hedge fund inflows and outflows. Therefore, in order to detect movements in alpha in response to flows, we require a sufficiently lengthy time period in our estimation. However, in order to avoid a huge number of right hand side variables in our specifications, we constrain the coefficients on lags of one to 12 months to be the same, summing these lags of the right hand side variables in our equations. Since the alphas are estimated using returns from period $t-1$ to $t-12$, the flows are lagged an additional 12 months, and summed over the following 12 month period, $t-13$ to $t-24$ in order to avoid using overlapping observations.

All our standard errors are computed using the method of Newey and West (1987). These standard errors are consistent in the presence of heteroskedastic and autocorrelated residuals. We use six lags of the dependent variables and residuals when computing the Newey-West correction in our factor regressions, and eighteen lags of the dependent variables and residuals when computing the Newey-West correction in our flow regressions. These are the maximum numbers of lags that we can use taking into account the number of observations and the sub-period breaks in our specifications.

[4]Ackermann, McEnally and Ravenscraft (1999) find that incentive fees rarely change over a fund's life.

[5]We also do the analysis using six monthly lags, and the results are not greatly altered.

4 Results

4.1 Alpha Attenuation

Table III presents the results from estimating regression (4) for the entire period as well as for the three sub-periods. The first row in each strategy shows estimates of equation (4) for the overall period, and the subsequent three rows show estimates of equation (4) for the three sub-periods. There are several features of note in the table. First, the regression R^2 statistics range between 33 and 78 percent across strategies over the entire sample period. Clearly, a large fraction of hedge fund returns can be explained using a linear factor model. While these R^2 statistics appear low in contrast to those observed in mutual funds (see Carhart (1997)), they are higher when we account for the change in exposures in different sample periods. Second, for five out of eight strategies, the alpha over the entire sample period is positive and statistically significant at the five percent level. These (net-of-fee) alphas range from 31 to 44 basis points per month in excess of the risk-free interest rate. Hedge funds, over the entire eleven-year period from 1994 to 2004, appear to have delivered returns in excess of their systematic risk exposures. Third, the systematic risk exposures are quite startling. For all but the 'Other' category of hedge funds, the exposure to the excess return on the market portfolio and to the small-minus-big factor is large, positive and statistically significant. An investor could take exposure to these factors far cheaper than by incurring the high management and incentive fees implicit in hedge fund investments. Exposure to the market could easily be achieved by buying an ETF, while exposure to SMB could be achieved by purchasing a small-cap mutual fund.[6]

The full-sample alpha and systematic risk exposures disguise interesting time-variation over the sample period. The three rows below the full-sample coefficient estimates present the risk exposures and alphas over the three time periods in the data, January 1994 to September 1998 (period I), October 1998 to March 2000 (period II) and April 2000 to December 2004 (period III).

First, the Chow structural break test strongly confirms the hypothesis that there are three distinct periods in the data, over which systematic risk ex-

[6]Bams and Otten (2002) find that European small-cap funds exhibit positive post-fee alpha.

posures change greatly. Second, the estimated alpha is largest in period II. For example, in the Security Selection, Relative Value, Directional Traders and Multi-Process strategies, the estimated alpha in period II is greater than 80 basis points per month over the 18 month period. Third, alpha has fallen in the most recent sub-period in the data, relative to the period II alpha, as well as in contrast with period I alpha. For example, in Security Selection, Directional Traders, Fixed Income and Relative Value strategies, alpha is either far lower than that in period II, or not statistically significant. This finding echoes that found in Fung et al. (2007), who discover the same downtrend in alpha using data on funds-of-funds.

What has been responsible for this reduction in alpha? Table IV presents a clue: we compute the average monthly flow as a percentage of last month's AUM at the strategy level for the three sub-periods. The table reveals that for every strategy, the flow means have been higher in the third sub-period than in the second sub-period, and in most cases, also substantially higher than those in the first sub-period. Capacity constraints may be the answer to the reduction in alpha witnessed in Table III. For a more formal analysis, we now turn to estimates of equation (??) to see whether we can detect the presence of capacity constraints in hedge fund strategies using hedge fund flows and rolling alpha estimates.

4.2 Capacity Constraints

Table V presents the results of our capacity constraints regressions. First, the coefficient on lagged flows, whenever it is statistically significant, is negative. This is true for four out of the eight strategies in the set, Relative Value, Emerging Markets, Fixed Income and Directional Traders strategy groups. The negative and statistically significant coefficients suggest the presence of capacity constraints in these strategies – when flows into the strategy have been previously high, the alpha in the subsequent period is likely to be lower. It seems intuitive that these constraints should bind for Relative Value, Fixed Income and Emerging Markets strategies, since these strategies rely on liquidity in their underlying markets (especially in the case of Emerging Markets). However, it seems less intuitive that these constraints bind for Directional Traders. One possible explanation is that there may be a lot of directional funds focusing on the same sector, creating a shortage of investment opportunities.

It is worth noting that unlike mutual funds, hedge funds may choose to close for new money. This makes it more difficult to find a relationship between flows and subsequent alpha, biasing the coefficient ϕ towards zero. Despite this bias, we are able to find evidence consistent with the presence of capacity constraints in hedge fund strategy flows and returns.

The coefficient magnitudes indicate that a ten percent increase in annual flows into a strategy is associated with a decline of between 36 and 94 basis points in alpha in the subsequent month. Across all funds, the alpha over the entire period from 1994 to 2004 is estimated to be approximately 25 basis points per month from Table III. This suggests that capacity constraints are economically important, not merely statistically significant. Taken at face value, our results suggest that if a strategy experiences steady asset growth for several years, the alpha could turn negative. In the factor regressions negative alphas are observed for some periods. Also, Aragon (2007) argues that when lock-ups are controlled for, the alpha may become negative. However, this is not a straightforward conclusion. Much would depend on how inflows are distributed across funds within a strategy, and the incidence of funds liquidating.

In table V the coefficients on size and size squared are consistent with the presence of diminishing returns to scale when significant (for two out of the eight strategies), consistent with the findings in Getmansky (2004). For a majority of the strategies, competition has a significant effect on performance. The effect is positive for Relative Value, Fixed Income, Directional Traders and Other strategies, suggesting that with higher competition, managers perform better. For Emerging Markets, however, competition has a negative effect on performance, which is in accordance with the analysis of Getmansky (2004).

Table VI presents the results when *alpha_u* is estimated from a four-factor model rather than the seven-factor model. Our results concerning capacity constraints are robust for the Relative Value, Fixed Income and Directional Traders strategy groups, although they do not hold for the Emerging Markets strategy.

One potential concern is the possibility of time-trends in our measures.[7] Figure 2 plots the time-evolution of the value-weighted *alpha_u* and flows for all strategies. The figure suggests that there is no time-trend in *alpha_u* over the sample period. An augmented Dickey-Fuller test confirms that the time-series of *alpha_u* is stationary. Furthermore, there is no linear upward trend in flows, so there is no need to detrend the variable. Finally, we calculate the Durbin-Watson statistic in our regressions, and obtain values that are always close to two, indicating that the residuals are not autocorrelated.

An integral part of Berk and Green's argument is that high ability managers will benefit from increased fees. We investigate whether there is an increase in fees over our sample period. Table VII shows both AUM weighted and equally weighted incentive fees over the period from 1994 to 2004. The first half of the table reveals that there has been a near-monotonic increase in incentive fees over the period. Funds born in 2004 have an average incentive fee of 19.32 percent. This represents a substantial increase from 1994, when the comparable number is 15.80 percent. For all funds (not merely those born each year), on an equal-weighted basis, there has been an increase of approximately 152 basis points in incentive fees over the same period.

The value-weighted measures in Table VII show a similar trend, with an increase in incentive fees of approximately 200 basis points over the same ten year period. Interestingly, there appears to be no similar trend in the management fee component. Taken together, the results in Table VII provide additional evidence that the Berk and Green (2004) model is an accurate characterization of the hedge fund industry.

5 Conclusions

This paper documents trends in the systematic risk exposures and alphas of hedge fund strategy index returns. The analysis reveals that alpha generation occurred primarily during the peak of the bull market period between October 1998 and March 2000. Furthermore, alpha in the hedge fund industry has severely declined in the most recent sub-period in the

[7] We thank an anonymous referee for pointing this out.

data, from April 2000 to December 2004. We attempt to uncover whether capacity constraints in the hedge fund industry are responsible for the recent decline in the alpha of hedge fund strategies. We find that for four out of eight hedge fund strategies, capital inflows have statistically preceded negative movements in alpha.

Taken together, our results suggest that capacity constraints do exist at the level of hedge fund strategies, and are likely to be a concern for investors going forward.

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Table I
Summary Statistics

This table presents summary statistics for assets under management (AUM), the number of funds and capital flows across eight hedge fund strategies. The columns in panel 1 represent the strategies, and the rows show the percent of total AUM that is contained within each strategy at the end of each year. The final column presents the total AUM contained across all strategies at the end of each year in billion of US dollars. Panel 2 presents the number of funds at the end of each year for each strategy represented in columns. The final column of Panel 2 contains the total number of funds in our sample at the end of each year. Panel 3 presents the percent of total net flow into the hedge fund industry for each strategy, for each year. The final column presents the total net dollar flow in billions of US dollars.

				Panel 1: Composition of Total AUM					
Year	Security Selection	Macro	Relative Value	Directional Traders	Multi-Process	Emerging Markets	Fixed Income	Other	Total U.S. $BN
1994	11%	35%	5%	15%	7%	10%	5%	10%	69.257
1995	12%	30%	6%	20%	8%	9%	5%	10%	86.142
1996	13%	28%	7%	21%	8%	9%	7%	7%	135.767
1997	14%	24%	8%	19%	9%	10%	8%	7%	206.194
1998	20%	20%	10%	20%	9%	4%	10%	8%	220.332
1999	23%	16%	10%	21%	9%	4%	8%	9%	276.613
2000	24%	8%	14%	24%	10%	3%	8%	10%	292.249
2001	27%	4%	18%	19%	10%	2%	9%	10%	344.168
2002	27%	4%	19%	17%	11%	2%	10%	10%	392.965
2003	28%	5%	18%	16%	10%	3%	9%	11%	570.436
2004	26%	5%	17%	16%	13%	3%	9%	12%	739.371
				Panel 2: Composition of Number of Funds					**Number**
1994	13%	18%	7%	15%	6%	7%	6%	27%	1115
1995	13%	17%	8%	17%	8%	9%	5%	23%	1464
1996	15%	15%	9%	20%	8%	9%	5%	18%	1954
1997	17%	14%	9%	21%	9%	10%	5%	16%	2312
1998	19%	12%	10%	22%	9%	8%	5%	13%	2523
1999	20%	11%	11%	24%	8%	7%	5%	13%	2811
2000	20%	9%	13%	27%	9%	6%	5%	12%	3075
2001	20%	7%	16%	28%	9%	4%	4%	12%	3357
2002	20%	6%	18%	27%	10%	3%	5%	11%	3713
2003	21%	6%	17%	26%	10%	3%	5%	12%	4009
2004	23%	6%	16%	22%	12%	3%	5%	13%	4091

Table I
Continued.

Panel 3: Composition of Net Flows									
Year	**Security Selection**	**Macro**	**Relative Value**	**Directional Traders**	**Multi-Process**	**Emerging Markets**	**Fixed Income**	**Other**	**Total US$ BN**
1994	2%	4%	-2%	27%	20%	35%	11%	2%	3.069
1995	44%	-138%	154%	62%	49%	-48%	-2%	-21%	0.508
1996	10%	7%	19%	23%	17%	6%	14%	4%	8.819
1997	14%	8%	17%	16%	10%	10%	12%	13%	24.720
1998	29%	6%	20%	13%	13%	-5%	17%	7%	17.422
1999	15%	2%	36%	53%	-3%	-12%	1%	8%	9.314
2000	26%	-1%	32%	35%	10%	-1%	1%	-3%	23.889
2001	26%	3%	33%	14%	14%	0%	4%	6%	35.127
2002	25%	2%	22%	18%	14%	2%	9%	8%	37.588
2003	11%	8%	22%	20%	15%	2%	9%	14%	80.837
2004	17%	5%	14%	20%	15%	4%	11%	14%	100.829

Table II
Summary Statistics: Returns and Flows

This table presents summary statistics for hedge fund strategy returns and flows. For each strategy represented in a column, in rows we present the number of funds, the average life of a fund in years and the time series mean of total AUM across all funds in the strategy. This is followed by summary statistics for AUM weighted returns (in excess of the three-month T-bill rate) across all funds in each strategy, and total flows as a percentage of strategy AUM. The summary statistics in each case are: the annualized mean, median and standard deviation. The standard deviation is annualized by multiplying the square root of 12 under the assumption that monthly returns are iid. Strategy level flows are calculated by aggregating individual fund flows up to the level of strategies, and scaling the dollar flows by strategy-aggregated end-of-previous-month AUM.

	Security Selection	**Macro**	**Relative Value**	**Directional Traders**	**Multi-Process**	**Emerging Markets**	**Fixed Income**	**Other**
N(Funds)	1711	796	970	1455	699	423	399	1157
Average Life in Years	4.0	4.4	4.4	5.1	4.7	4.4	4.3	4.7
Average AUM (US $BN)	60.9	30.7	40.3	51.0	27.5	11.5	23.9	27.1
Excess Returns								
μ	6.481	4.987	5.610	8.378	7.960	5.951	2.758	5.191
Median	6.077	4.824	6.225	5.893	8.883	15.127	4.960	4.301
σ	6.522	9.430	2.630	9.075	5.273	16.386	4.182	7.240
Flows								
μ	8.955	6.290	18.292	11.101	13.751	4.784	11.320	9.187
Median	7.800	3.919	18.756	10.767	12.282	5.347	9.823	8.547
σ	3.656	3.581	4.552	3.197	4.125	5.027	4.203	4.565

Table III
Value Weighted Index: Factor Regressions

The left hand-side variable in each regression is the AUM weighted (net-of fee) excess return of hedge funds within a strategy. The right hand-side variables are: the excess return on the S&P500 index; the excess of small-cap over large-cap stock returns constructed using the Wilshire indices; excess returns on three portfolios of lookback straddle options on bonds, commodities and foreign exchange; the spread of Moody's BAA corporate bond returns index over the U.S. 10-year maturity treasury bond, and finally the excess return of the U.S. 10-year maturity treasury bond. For strategies in rows, in columns we present the intercept alpha, the slope coefficients on the seven factors and the R-squared statistic from the regression. Newey-West heteroskedasticity and autocorrelation consistent standard errors are employed (using 6 lags), two stars indicate significance at the 5% level, and one star indicates significance at the 10% level. The regression results are reported first for the overall sample and then for three sub-periods; January 1994 to September 1998 (period I), October 1998 to March 2000 (period II) and April 2000 to December 2004 (period III). The last two columns in the table present the results from testing for two sample breaks; between period I and period II and between period II and period III. Test for structural breaks are conducted using the Chow (1960) test, and is applied only to slope coefficients, not the constant term. The value of the F-statistic is shown in the table below and the critical value (alpha=0.05) is 2.167.

Returns	α	Rm-Rf	SCMLC	PTF Bonds	PTF Com	PTF FX	BAA Spread	TCM 10 Y	R^2	I=II?	II=III?
All Funds											
Overall period	0.249**	0.259**	0.199**	-0.012	0.018	0.011**	0.177	0.168**	0.586		
Period I	0.125	0.382**	0.121**	-0.012	0.035**	0.012**	0.471*	0.022	0.675		
Period II	0.549**	0.269**	0.366**	0.063**	-0.007	-0.024*	0.753**	0.512**	0.884	2.869**	22.834**
Period III	0.147*	0.193**	0.151**	0.000	0.017**	0.012**	0.091	0.155**	0.769		
Security Selection											
Overall period	0.309**	0.303**	0.272**	-0.006	0.014	0.005	-0.038	0.098*	0.668		
Period I	0.288**	0.371**	0.293**	-0.006	0.025**	0.003	0.184	0.052	0.834		
Period II	0.916**	0.431**	0.435**	0.049**	-0.006	-0.003	0.881**	0.563**	0.891	3.114**	27.073**
Period III	0.027	0.209**	0.167**	0.000	0.024**	0.007	0.024	0.103	0.718		
Macro											
Overall period	0.087	0.266**	0.158**	-0.013	0.025	0.017	0.438	0.313**	0.335		
Period I	0.404	0.344**	-0.113	-0.029	0.043	0.023	0.775	0.143	0.424		
Period II	-0.835	0.311	0.537**	0.153**	0.001	-0.072*	1.327*	0.868*	0.725	3.168**	14.376**
Period III	-0.071	0.262**	0.183**	0.011**	0.014	0.025**	0.050	0.216**	0.718		

Table III
Continued.

Returns	α	Rm-Rf	SCMLC	PTF Bonds	PTF Com	PTF FX	BAA Spread	TCM 10 Y	R^2	I=II?	II=III?
Relative Value											
Overall period	0.384**	0.045**	0.061**	-0.010	0.002	-0.001	0.160	0.023	0.331		
Period I	0.332**	0.091**	0.086**	-0.005	0.005	-0.005	0.574**	-0.013	0.613		
Period II	0.934**	-0.040	0.085**	0.029**	-0.001	-0.021**	0.312	0.322**	0.731	4.084**	5.457**
Period III	0.292**	0.040**	0.011	-0.003	-0.005	0.009*	0.139**	0.043**	0.390		
Directional Traders											
Overall period	0.332**	0.461**	0.393**	-0.004	0.020*	0.016**	-0.024	0.183**	0.777		
Period I	0.103	0.614**	0.363**	0.005	0.031**	0.011**	0.430*	0.035	0.871		
Period II	1.327**	0.449**	0.509**	0.017	-0.025**	0.013	0.467**	0.388**	0.928	2.232**	35.389**
Period III	0.077	0.359**	0.297**	0.007	0.033**	0.015*	0.029	0.227**	0.841		
Multi-Process											
Overall period	0.444**	0.176**	0.169**	-0.023**	0.007	0.001	0.276**	0.073*	0.600		
Period I	0.147	0.300**	0.153**	-0.014*	0.004	0.001	0.753**	-0.045	0.736		
Period II	0.826**	0.127**	0.172**	0.009	0.009	-0.027*	0.247	0.169	0.764	2.172**	6.473**
Period III	0.472**	0.114**	0.157**	-0.012**	0.007	0.005	0.273**	0.068**	0.619		
Emerging Markets											
Overall period	-0.092	0.561**	0.412**	-0.036	0.005	0.002	0.720**	0.090	0.481		
Period I	-1.279**	0.839**	0.246	-0.037	0.022	-0.002	1.429*	-0.447	0.530		
Period II	0.677	0.794**	0.651**	0.107	-0.019	-0.062**	1.260	-0.048	0.708	0.648	11.293**
Period III	0.379	0.512**	0.306**	0.000	0.042	0.003	0.470**	0.349**	0.696		
Fixed Income											
Overall period	0.039	0.121**	0.117**	-0.008**	0.005	0.000	0.349**	0.105**	0.530		
Period I	0.064	0.175**	0.062	-0.007	0.004	0.007	0.160	-0.080	0.489		
Period II	0.402**	0.018	0.122**	0.035**	0.002	-0.039**	1.107**	0.782**	0.898	5.485**	12.138**
Period III	0.030	0.127**	0.098**	-0.009	0.006	0.002	0.316**	0.137**	0.685		

Table III
Continued.

Returns	α	Rm-Rf	SCMLC	PTF Bonds	PTF Com	PTF FX	BAA Spread	TCM 10 Y	R^2	I=II?	II=III?
Other											
Overall period	0.392**	0.031	-0.030	0.030**	0.039*	0.036**	0.089	0.221**	0.379		
Period I	0.338	0.074	-0.106	0.037**	0.105**	0.031**	-0.047	0.104	0.622		
Period II	-0.153	0.096	0.136	0.071**	-0.002	0.018	0.073	-0.064	0.367	3.175**	1.606
Period III	0.409**	0.044	0.028	0.005	0.003	0.032**	-0.135	0.236**	0.372		

Figure 1: Number of Funds and Total AUM

This figure plots the evolution of the number of hedge funds and the total AUM in our sample across time in months. The data are constructed by aggregating information from TASS, HFR, CISDM and MSCI for all funds that report AUM. The data begin in January 1994, and end in December 2004.

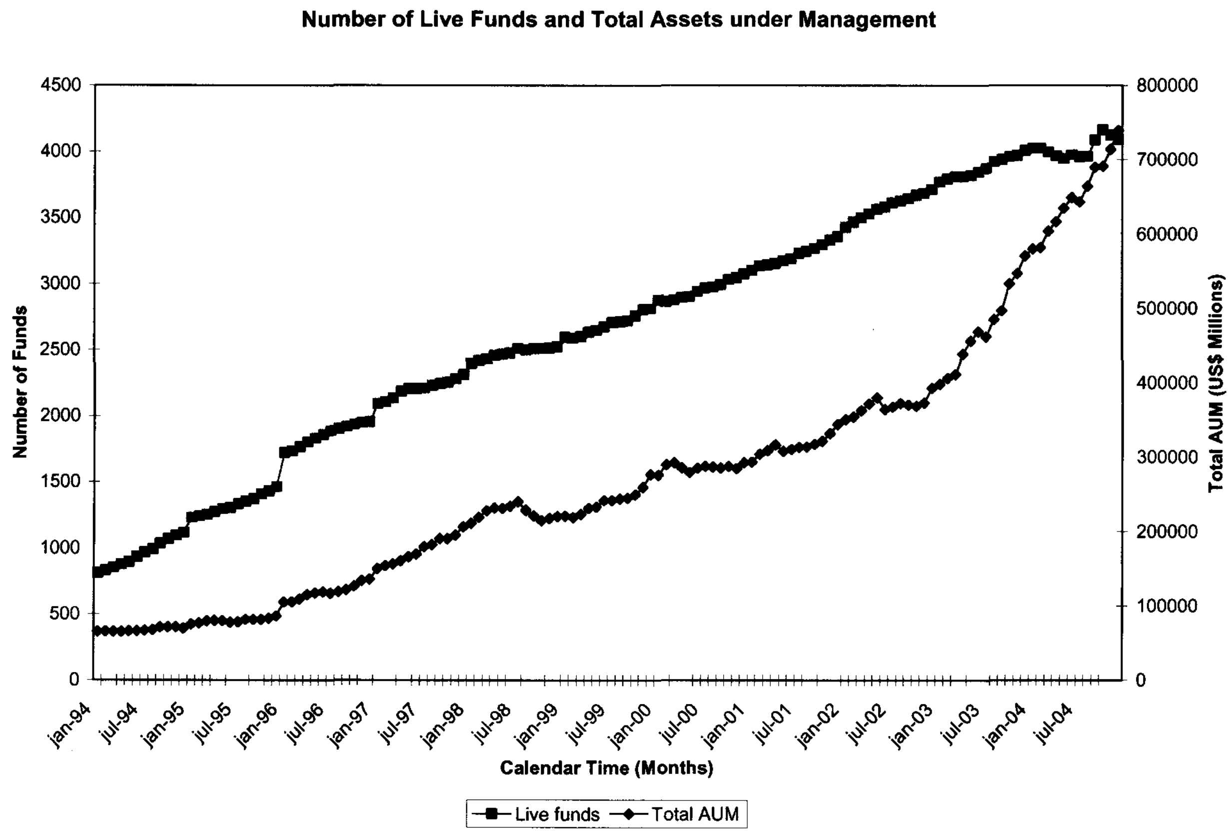
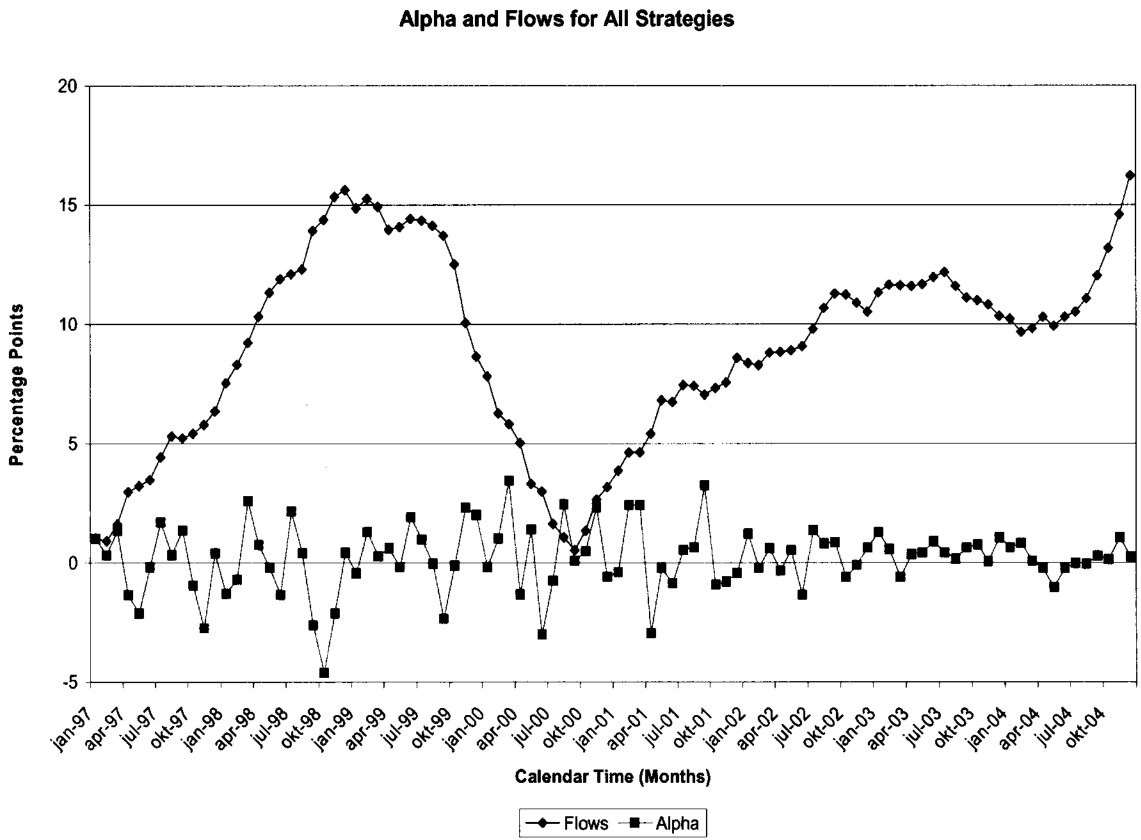


Figure 2: Alpha and Flows for All Strategies

This figure plots the evolution of the value-weighted non-systematic return and flows for all strategies in our sample across time measured in months. The data are constructed by aggregating information from TASS, HFR, CISDM and MSCI for funds that report AUM. The data begin in January 1997, and end in December 2004.



Chapter 4

Optimizing over Hedge Fund Indices: Naive versus Optimal Portfolios

Maria Strömqvist*

Abstract

This paper investigates the out-of-sample performance of five allocation models relative to an equally weighted portfolio, when optimizing over hedge fund strategies. Unlike in DeMiguel et al. (2007), the findings show that for hedge fund investors the naive allocation model (1/N) with equal weights in each asset is not an efficient allocation. The risk-adjusted performance can be improved by using an optimal sample-based allocation model such as the Bayes-Stein portfolio or the optimal 3-fund portfolio. Moreover, significant improvement in out-of-sample alpha can be made if the investor optimizes over non-systematic returns instead of total returns, which is an important results for investors seeking alpha. The investors can almost double the yearly out-of-sample alpha of the portfolio from 4.6 percent to 8.4 percent, an increase which is of economic significance. The allocation models are also compared to the observed allocation, proxied by the distribution of assets under management between hedge fund strategies in the sample. The results show that the observed allocation is efficient in terms of alpha, especially during the first half of the sample period.

Keywords: *Hedge funds; portfolio choice; asset allocation; alpha*

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1 Introduction

This paper investigates the out-of-sample performance of five allocation models relative to an equally weighted portfolio, when optimizing over hedge fund strategies. In a recent paper by DeMiguel, Garlappi and Uppal (2007), it is shown that the naive 1/N allocation rule often performs as well or better than advanced optimization models regarding equity portfolios. However, hedge funds' dynamic trading strategies create different risk and return characteristics than other investments. The question is if the result in DeMiguel et al. (2007) is also true for portfolios of hedge funds. That is, can the out-of-sample performance (and especially alpha) of hedge fund portfolios be improved by using optimal asset allocation models?

The findings show that for a hedge fund investor, the naive portfolio allocation model (1/N) with equal weights in each asset is not an efficient allocation. The risk-adjusted out-of-sample performance can be improved by using an optimal sample-based allocation model. The result holds, notwithstanding if the optimization model takes estimation error into account. This conclusion differs from the findings in DeMiguel et al. (2007), where the gain from using sophisticated optimization models is offset by estimation errors.

Although the 1/N allocation has a higher average return than the optimal allocation models, it underperforms when risk is taken into account. The out-of-sample return series of the equally weighted portfolio has a high variance. The volatility is better managed by the optimal portfolio techniques than the 1/N allocation, thus generating benefits in risk-adjusted evaluation metrics.

More importantly, the results reveal that the out-of-sample alpha can be significantly improved by optimizing over non-systematic returns instead of total returns, which is an important result for investors seeking absolute returns on their investments. The investors can almost double the yearly out-of-sample alpha from 4.6 percent to 8.4 percent by optimizing over non-systematic returns. The increase is of economic significance.

The performance of the allocation models in terms of alpha is compared to that of the observed allocation, proxied by the distribution of assets under management between the hedge fund strategies in the sample. The analysis reveals that the observed allocation is efficient, especially in the first part of the sample period.

The portfolio optimization results display that the optimal weights in hedge fund strategies are far from the equal weights in the naive allocation model. The hedge fund portfolio is dominated by the Relative Value strategy due to its relative high return and low variance. The optimization also reveals that only a few percent (if any) of the portfolio should be invested in equity.

The benefits from using optimization techniques are mainly achieved when using an expanding window to estimate the required inputs. The expanding window starts with three years of historical data and then incorporates an additional quarter of data in each estimation. Thus, it takes all available historical data into account in the estimation. This is especially valuable for hedge funds that have a short return history.

The paper by DeMiguel et al. (2007) uses seven empirical datasets consisting of U.S. equity portfolios (for example industry portfolios and portfolios sorted on size and book-to-market) and country equity indices. They evaluate the out-of-sample performance of fourteen allocation models relative to the naive 1/N portfolio. They find that no model is consistently better than the 1/N rule in terms of Sharpe ratio, certainty-equivalent return or turnover.

DeMiguel et al. (2007) is not the first paper to evaluate the performance of an equally-weighted portfolio. Bloomfield, Leftwich and Long (1977) show that sample-based mean-variance optimal portfolios do not outperform an equally weighted portfolio, and Jorion (1991) found that the equally weighted and value-weighted indices have an out-of-sample performance similar to that of the minimum-variance portfolio and the tangency portfolio obtained with Bayesian shrinkage methods.

There is some empirical evidence that investors use simple asset allocation rules such as 1/N when investing. Benartzi and Thaler (2001) document that investors allocate their wealth across assets using the naive 1/N rule. Huberman and Jiang (2006) find that participants tend to invest in only a small number of the funds offered to them and allocate their wealth evenly across the funds chosen. However, this literature is focused on individual investors. Assuming that the average hedge fund investor is a sophisticated investor, it is not clear that the naive allocation model is used by such an investor. Even if hedge fund investors do not use these simple heuristics, it is still interesting to get an idea of the value of advanced optimization techniques in hedge fund investing.

The use of mean-variance methodology to evaluate hedge fund performance has been questioned because of the non-normality in returns. Although the return of individual hedge funds can be far from normally distributed, it is important to notice that at the aggregate level, hedge fund strategy returns (with the exception of Multi Process) are not less normally distributed than equity portfolios such as industry portfolios or the Fama-French portfolios.

McFall Lamm Jr (2003) investigates the optimization over thirteen hedge fund strategies using the mean-variance framework and models that take asymmetric distributions into account. He finds that incorporating asymmetry produces different hedge fund portfolios than in the situation when returns are symmetric. It is mainly the strategies that have negative skewness and excess kurtosis, such as Distressed Debt and Merger Arbitrage, that receive a lower allocation when asymmetry is taken into account.

On the other hand, Levy and Markowitz (1979) and Hlawitschka (1994) show that mean-variance ranking of mutual funds is highly correlated with the ranking based on the true utility function. Fung and Hsieh (1999) confirm that this result also holds for hedge funds. And Cremers, Kritzman and Page (2005) find that higher moments of hedge funds do not meaningfully compromise the usefulness of mean-variance optimization if investors have power utility.

The rest of the paper is outlined as follows. The next section presents the data and some summary statistics. Section 3 describes the asset allocation models and the portfolio optimization and section 4 the performance evaluation metrics. The results are presented in section 5 and the last section concludes.

2 Data and Summary Statistics

In this paper, hedge fund data from four large databases are used; HFR, TASS, CISDM and MSCI, giving a representative sample of the hedge fund industry. The monthly data begin in January 1994, and end in December 2004, and include dead funds. Only funds that report assets under management (AUM) are included in the dataset. Funds-of-hedge-funds are excluded from the sample as well as any fund with flows greater (less) than 500 (100) percent of the AUM of its prior month at any point in its history.[1] The total dataset consists of about 7600 hedge funds.

Fung and Hsieh (1997) and Brown and Goetzmann (2003) have shown that there are up to eight style factors in hedge fund returns. Following the classification in Naik, Ramadorai and Strömqvist (2007), funds are classified into eight broad strategies. However, Emerging Market hedge funds are excluded from the analysis because they have been thoroughly investigated in Strömqvist (2007). The optimization results in Strömqvist (2007) show that an investor should not allocate any capital to the emerging market strategy. Hence, excluding this strategy will not affect the results.

Thus, in this paper, seven broad hedge fund strategies are used. They are the following: Security Selection, Macro, Relative Value, Directional Traders, Multi Process, Fixed Income and Other. A detailed description of the strategies and the type of funds contained in each is given in Table I.

Value-weighted excess return indices are computed at a strategy level and are constructed as

$$r_{st}^{VW} = \sum_{i=1}^{N} w_{it}(r_{it} - r_{ft}) \tag{1}$$

where

$$w_{it} = AUM_{it-1} / \left(\sum_{i=1}^{N} AUM_{it-1} \right) \tag{2}$$

[1]Extreme flows indicate that there is a problem with the AUM data. This is mainly an issue for very small funds.

are AUM weights reconstructed each month, r_{it} is the net-of-fee return on fund i in month t, r_{st} is the return in month t for strategy s and r_{ft} is the return of the three-month U.S. Treasury Bill in month t. The strategy returns are corrected for serial correlation using the methodology in Getmansky, Lo and Makarov (2004).

Table II presents summary statistics regarding the strategies in the sample. The largest strategy is Security Selection consisting of 1700 funds and the smallest is Fixed Income with 400 funds. The average life of a hedge fund is approximately the same for all strategies, i.e. between four and five years. Regarding the performance fees charged, the Fixed Income Strategy has the lowest fee (16.8 percent) and Other has the highest (19.3 percent). Moreover, only five percent of the Macro Funds employ lockup periods, while the corresponding number for Directional Traders is 36 percent.

To calculate the systematic component, strategy returns are regressed on the factors in Fung and Hsieh (2004). The model comprises two equity factors (S&P 500 and a small capitalization factor), a credit spread factor and a long-term bond factor. In addition, the model has three portfolios of lookback straddle options on currencies, commodities and bonds. The option factors are constructed to replicate the maximum possible return of a trend-following strategy on the underlying asset.

Alternative factor models are the Fung and Hsieh (2004) model without the three option factors and the four-factor model consisting of the three Fama and French (1996) factors (S&P 500, HML, SMB) and the Carhart (1997) momentum factor. Data for the Fung and Hsieh (2004) factors are collected from David Hsieh's website and data for the Fama and French (1996) and Carhart (1997) factors are collected from Kenneth French's website.

3 Description of Asset Allocation Models and Portfolio Optimization

In the paper, the simple allocation of equal weights in all assets is compared to optimal allocation strategies. The term "optimal allocation strategies" is used for models that take advantage of historical data and use optimization techniques to determine the portfolio weights. The allocation models are described below. The resulting portfolios are also compared to the observed allocation as proxied by the distribution of assets under management in hedge fund strategies in the sample.

3.1 Naive Portfolio Allocation

The naive portfolio allocation is an equally weighted portfolio with N assets. The portfolio is rebalanced every quarter to keep equal weights in all assets. Obviously, the allocation model does not involve any optimization or estimation and does not take the data into consideration. However, it can be considered as a contrarian trading strategy, which is based on the assumption of negative serial correlation of prices.[2] Hence, the weights in assets that performed poorly in the previous period are increased and the weights in assets that performed well in the last period are decreased. Calvet, Campbell and Sodini (2007) find evidence of Swedish investors actively rebalancing their portfolio to keep the target portfolio weights.

3.2 Optimal Allocation Models

Five optimal allocation models are used to estimate the portfolio weights. The five models are briefly presented below. A detailed description of the allocation models and the implementation can be found in the appendix.

1. *Mean-variance portfolio*: The goal of the mean-variance portfolio is to produce portfolio weights that offer the highest Sharpe ratio. It requires estimation of the expected return vector and the covariance matrix.
2. *Minimum-variance portfolio*: The goal of the minimum-variance portfolio is to choose portfolio weights that provide the lowest portfolio variance. It only requires estimation of the covariance matrix.
3. *Bayes-Stein shrinkage portfolio*: The Bayes-Stein shrinkage portfolio integrates estimation risk into the analysis. When estimating the expected return vector and the covariance matrix, it uses shrinkage estimators.

[2] If the portfolio is not rebalanced, it will instead be a momentum strategy, where better performing assets will receive a greater weight in the portfolio.

4. *Optimal "three-fund" portfolio*: The idea behind the optimal "three-fund" portfolio is to reduce the estimation error when obtaining the tangency portfolio. Including a second risky portfolio can diversify the estimation risk given that the estimation errors of the two risky portfolios are not perfectly correlated.

5. *Bayesian "Data-and-Model" portfolio*: Unlike the Bayes-Stein portfolio, the Data-and-Model portfolio does not only take the data into account but also the belief that asset returns are generated by a particular asset pricing model. The asset-pricing model considered is the Fung and Hsieh (2004) 7-factor model. In the implementation of the Data-and-Model approach, the investor is assumed to believe in the asset allocation model with a subjective probability of 50 percent. The Data-and-Model portfolio is *not* used when optimizing over non-systematic returns because it already uses the Fung and Hsieh (2004) model as the asset pricing model.

3.3 Portfolio Optimization

When performing the portfolio optimization, the portfolio weights are constrained to be positive and sum to one. The restriction on positive weights is natural because it is not possible to go short in hedge funds. The restriction on the weights summing to one assumes that the investor cannot borrow money.

The optimization is performed using monthly data, but portfolio weights are calculated quarterly. It is assumed that the portfolio weights stay the same during the next three months. This would not require any substantial rebalancing unless there are large movements in the returns at the strategy level during some months. This may be the case in extreme periods (like the end of 1998) but should be a reasonable assumption for most of the sample period.

The realized return series are calculated out-of-sample. That is, the resulting weights in one period are multiplied with the corresponding returns in the next period[3]. Transaction costs are not taken into consideration.

[3]The results are robust to the weights in period t being multiplied by the returns in $t+2$ instead of $t+1$.

Given that the comparison is done between models and that they rebalance the portfolio at the same frequency, the transaction costs should be approximately the same for all models.

The optimization is performed using total returns and non-systematic returns. The non-systematic returns are only used to estimate the optimal portfolio weights. The resulting weights are then (as when optimizing over total returns) multiplied with total returns in the next period. The non-systematic returns are calculated as total returns minus the systemic risk factors (βX_t). The coefficients (betas) are obtained by running a regression of hedge fund returns on the seven-factor model of Fung and Hsieh (2004). Hence, the following equation is estimated:

$$r_{st} = \alpha + \beta X_t + \varepsilon_t, \tag{3}$$

where r_{st} is the value-weighted strategy index return and X_t is a vector containing the seven factors in the Fung and Hsieh (2004) model. Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors are employed (with 6 lags).

Two windows are used for the estimation; a rolling three-year window and an expanding window. The three-year window moves three months between estimations while the expanding window includes an additional three months of historical data when estimating the required inputs each quarter. Given the short return history for hedge funds, it may be beneficial to use the expanding window because it takes advantage of all available data in the estimation.

4 Performance Evaluation and Inference

Four evaluation metrics are used to evaluate the performance of the different allocation models[4]. The performance of the allocation models is always evaluated out-of-sample.

The first metric is the mean for realized return series (r_{it}) which is calculated as

[4]DeMiguel et al. (2007) also use the certainty equivalent return as an evaluation metric. Certainty equivalent is not implemented here, because it is often negative for hedge fund portfolios due to the high variance.

$$\mu_s = \frac{\sum_{i=1}^{T} r_{it}}{T}.$$

Second, the out-of-sample Sharpe ratio for strategy s is defined as the sample mean of out-of-sample excess returns (over the risk free rate), μ_s, divided by the sample standard deviation, σ_s.

$$\text{Sharpe ratio}_s = \frac{\mu_s}{\sigma_s}.$$

Third, the gain-loss metric is the number of months with positive returns divided by the number of months with negative returns.

Finally, the risk-adjusted return or alpha is the intercept from regressing the realized return series on the Fung and Hsieh (2004) 7-factor model. To evaluate the robustness of the resulting alpha, the Fung and Hsieh (2004) 4-factor model and the Fama-French-Carhart 4-factor model are also implemented.

A standard t-test tests the hypothesis that the metric is equal to zero by using the bootstrapped standard errors. For all metrics, except the Sharpe ratio, a standard test of difference between two populations is performed using the bootstrapped standard errors. The hypothesis is that there is no statistical difference between the value of the metrics for the naive allocation model and the optimal allocation models. For the Sharpe ratio, the Jobson-Korkie test with the correction in Memmel (2003) is used.

5 Results

5.1 Hedge Fund Strategy Returns

Panel B in Table II summarizes the return distribution over the sample period for the seven strategies. The mean monthly returns range from 0.58 percent for Fixed Income to 0.98 percent for Directional Traders. Moreover, Multi Process has the highest median (0.96 percent per month) and Relative Value the lowest standard deviation. The minimum returns (except for Other) occur around the time of the collapse of the hedge fund

Long-Term Capital Management (LTCM) in 1998 and the maximum returns are earned around the peak of the high-tech bubble at the end of 1999 or at the beginning of 2000.

Panel B in Table II also displays the skewness and kurtosis[5]. Four out of seven hedge fund strategies have a negative skewness (Relative Value, Directional Traders, Multi Process and Fixed Income). A negative skewness implies that the strategy produces a greater number of above-average returns than a normal distribution, but negative outcomes tend to be lower than what would be expected from a normal distribution. The kurtosis is between two and four for many strategies except for Multi Process, which has a high kurtosis, and Other, which has a low kurtosis. To test whether the return series are normality distributed, the Jarque-Bera test is performed. Normality is rejected at the 5%-level for all strategies but Security Selection and Directional Traders. Moreover, a normal distribution is rejected for the S&P 500 index and the U.S. long-term bonds.

Although the return of individual hedge funds can have extreme properties, it is important to notice that at the aggregate level, hedge fund strategy returns (with the exception of Multi Process) are not less normally distributed than equity portfolios. Calculating the skewness and kurtosis for the monthly datasets available from Kenneth French's website over the same period (1994-2004), none of the SMB, HML or the momentum factor[6] are normally distributed. Moreover, none of the industry portfolios are normally distributed; they generally have negative skewness and a kurtosis between zero and one.[7]

Figure 1 plots the cumulative total return over the sample period for the seven hedge fund strategies, the S&P 500 index and the U.S. 10-year maturity Treasury Bond. The figure shows that the hedge fund strategies (except Fixed Income) had a similar development as the equity index until the end of the high-tech bubble in 2000. The equity index then performed worse than any of the hedge fund indices.

The Macro strategy performed well during the Asian crisis from the mid 1997 to the end of 1998, indicating that it was able to profit from the

[5]A normal distribution has a skewness equal to 0 and a kurtosis equal to 3.

[6]SMB: skew=-1.56, kurt=6.34, HML: skew=0.68, kurt=1.86 and Mom: skew=-0.64, kurt=4.46.

[7]These are some of the datasets used for optimization in DeMiguel et al. (2007).

turbulence in the Asian markets. In the following period, Macro was outperformed by Directional Traders and Security Selection. Multi Process performed especially well relative to the other strategies in the bull market from mid 2003 until the end of 2004. The Relative Value strategy has had a positive and smooth return throughout the period.

As expected, the long-term bond has the lowest return but also a low volatility. The Fixed Income strategy has performed better than the long-term bond, but the strategy still has a lower average return than other hedge fund strategies.

What is more interesting, however, is how the strategies have performed in risk-adjusted returns (alpha). Figure 2 plots the cumulative risk-adjusted return of the hedge fund strategies over the sample period. The Fixed Income strategy has the worst performance in terms of alpha and a value below 100 throughout the period. Directional Traders, which had the highest total returns, are outperformed by Other and Macro. The Relative Value strategy has a similar performance in alpha as in total returns; the strategy has a smooth upward sloping graph.

5.2 Portfolio Performance

In general, when optimizing over *total returns*, the 1/N strategy with rebalancing performs well when risk is not taken into consideration, but poorly when the evaluation metric corrects for risk. The results are shown in Table IV for the expanding window and in Table VI for the three-year window.

Regardless of which window is used, the naive allocation model has a statistically significant higher average out-of-sample return than the five optimal allocation models. However, for the expanding window, the optimal allocation models all have a higher Sharpe ratio than the equally weighted portfolio. The difference in Sharpe ratios is not statistically significant when only three years of historical data are used in the estimation. This indicates that three years of data are not enough to get sufficiently accurate sample moments.

Moreover, the gain-loss ratio is higher for all optimal allocation models for both windows. Hence, the realized return series from the optimal models have more months of positive returns relative to negative returns than the 1/N strategy. The gain-loss ratio is twice as high for the optimal models as for the naive model.

When calculating the risk-adjusted return (alpha) for the different portfolios, the alpha is statistically higher for all portfolios as compared to the naive strategy. The only exception is the Data-and-Model portfolio when using an expanding window. The highest monthly alpha is achieved with the Fama-French-Carhart model, which also has the lowest R-square, indicating that the fit is not as good as with the Fung and Hsieh (2004) model.

As an alternative, the portfolio weights are calculated using *non-systematic returns*. The weights are then multiplied with total returns. This does not change the return series of the 1/N strategy, because it does not depend on data.

Table VIII and X display the results using an expanding and a three-year window, respectively. The 1/N strategy still outperforms the optimal allocation models in average out-of-sample return (not adjusted for risk). However, the optimal allocation models have statistically significant higher Sharpe ratios and gain-loss ratios (with a few exceptions). The gain-loss ratios are somewhat lower as compared to when optimization was performed over total returns, but the Sharpe ratios are about the same magnitude.

When optimizing over non-systematic returns, given that there is some persistence in risk-adjusted returns, optimal portfolios would be expected to perform well in terms of out-of-sample alpha. This is true for the expanding window, where the monthly alpha increases from around 0.4 percent per month when estimating over total returns to 0.7 percent when using non-systematic returns. The increase is of economic significance for investors seeking alpha. In Strömqvist (2007), the average hedge fund generates about 0.4 percent alpha per month or 4.6 percent per year. By optimizing over non-systematic returns, the investor can almost double this number in her portfolio to 8.4 percent per year. However, there is no such effect when using the three-year window, which once more signals that the three-year window is too short to achieve the full benefits of the optimization.

5.3 Optimal Portfolio Weights

The optimal portfolio weights for the five optimal allocation models, when optimizing over *total returns*, are shown in Table V for the expanding window and Table VII for the three-year window. The optimal portfolios are very different from the equally weighted portfolio of the 1/N strategy. The two tables both give the same conclusion: the optimal hedge fund portfolio is dominated by Relative Value. Between 70 and 80 percent of the portfolio should on average be invested in Relative Value over the period. This is due to the relatively high return and low volatility of this strategy. The weight is between 40 and 60 percent at the beginning of the period (depending on which allocation model is used) and then increases up to 80 percent at the end of 2004.

The weight in equity is only a few percent throughout the period. This is consistent with the conclusion in McFall Lamm Jr (1999) which suggests that investors should invest all their wealth in hedge funds.

There are greater differences in optimal weights between the models when using non-systematic returns. In Table IX (expanding window), the minimum-variance portfolio has an average weight of less than 50 percent in Relative Value while the mean-variance portfolio has an average weight of 75 percent in the same strategy. At the beginning of the period, the weight in Security Selection is as high as 33 percent in the minimum-variance portfolio.

The results for the three-year window in Table XI are similar, but Macro is allocated a substantial weight in the last part of the sample period. Both the minimum-variance model and the optimal 3-fund portfolio allocate a weight of 20 percent to Macro. Moreover, when optimizing over non-systematic returns, the weight in the long-term bond is lower than with total returns. However, investments in hedge fund strategies still dominate investments in equity.

McFall Lamm Jr (2003) pointed out that in the mean-variance framework, a higher weight will be given to strategies that have negative skewness and excess kurtosis. In this sample, this might be the case for Multi Process and to a lesser extent Relative Value. Multi Process is only given some weights at the beginning of the sample period when optimizing over total returns. Given that Relative Value does not suffer from extreme kurtosis (see Table

II), it appears that the conclusions regarding the portfolio allocation are robust to any potential upward bias due to non-symmetry in returns.

5.4 Optimal versus Observed Allocation

The observed allocation is inferred from the dataset. It is assumed that the average well-diversified hedge fund investor (or fund-of-funds) holds a portfolio similar to the distribution of assets under management among strategies.

The observed allocation at the end of each year is shown in Table III. There has been an almost exponential growth in assets under management in the hedge fund industry during the last decade. For the seven strategies in the sample, total assets under management have increased from 62 billion U.S. dollars in 1994 to over 700 billion U.S. dollars in 2004. Table III reveals that the allocation has shifted during the sample period. In 1994, Macro was the dominant strategy with 40 percent of the assets under management. The corresponding number for Macro in 2004 is 6 percent. Instead, Security Selection has increased its share of assets under management from 13 percent in 1994 to 30 percent in 2004. The Relative Value, Multi Process and Fixed Income strategies have all increased their share over the sample period, while Directional Traders and Other have had a stable proportion of the assets under management throughout the period. On average, the hedge fund investor is reasonably well diversified.

Figure 3 plots the cumulative risk-adjusted returns of the 1/N allocation strategy, four optimal allocation models (optimizing over non-systematic returns and using the expanding window) and the observed allocation. The figure compares the development of the portfolio alpha between an investor that only invests in hedge funds (as suggested by McFall Lamm Jr (1999)) and an investor that diversifies her hedge fund portfolio with equity and bonds according to optimal allocation models.

Figure 3 reveals that the observed allocation performs better than all the other allocation models during the first half of the sample period. Although it still performs well, the mean-variance and Bayes-Stein portfolios perform better in the latter part of the sample period. Hence, the average well-diversified hedge fund investor (or fund-of-funds) appears to have an efficient portfolio allocation. The 1/N strategy performs equal to or worse than the other strategies in terms of risk-adjusted returns.

6 Conclusions

This paper investigates the out-of-sample performance of five portfolio allocation models on a portfolio consisting of seven broad hedge fund strategies, equity and bonds. The analysis shows that for hedge funds, the naive portfolio allocation model with equal weights in each asset is not efficient. The risk-adjusted performance can be improved by using an optimal allocation model that takes data into account, despite the fact that these models suffer from estimation errors. The 1/N portfolio has a higher out-of-sample mean return than the other models, but performs worse when risk is taken into account.

Moreover, the results reveal that the out-of-sample alpha can be significantly improved by optimizing over non-systematic returns, which is an important result for investors seeking absolute returns on their investments. And, finally, only a few percent (if any) of the portfolio should be invested in equity.

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A Appendix: Asset Allocation Models

A.1 Mean-Variance Portfolio

The formula for calculating the mean-variance portfolio weights is the following:

$$\max w' \mu - \frac{\gamma}{2} w' \Sigma w \tag{4}$$

$$s.t \;\; 0 \leq w \leq 1 \tag{5}$$

$$\sum_{i=1}^{N} w_i = 1 \tag{6}$$

where w is the matrix of portfolio weights, μ is the matrix of expected excess return over the risk free rate and Σ is the corresponding variance-covariance matrix. The coefficient of relative risk aversion, γ, is assumed to be equal to one[8]. The portfolio weights are constrained to be non-negative and to sum to one, in order to be able to compare them with the observed allocation.

Thus, the model requires estimation of the expected returns vector (μ) and the variance-covariance matrix (Σ). Following DeMiguel et al. (2007), the following sample moments are used:

$$\mu^{MV} = \frac{1}{T} \sum R_t \tag{7}$$

$$\Sigma^{MV} = \frac{1}{T - N - 2} \sum (R_{i,t} - \overline{\mu})(R_{i,t} - \overline{\mu})' \tag{8}$$

where T is the number of observations and N is the number of assets. Σ^{MV} is not an unbiased estimator of Σ, but it is an unbiased estimator of Σ^{-1}.

The optimal portfolio weights are given by

$$w^{MV} = (\Sigma^{MV})^{-1} \mu^{MV} \tag{9}$$

[8]In DeMiguel et al. (2007) they perform a sensitivity analysis using different values for the risk aversion coefficient. They conclude that the results are not sensitive to the choice of gamma.

The mean-variance portfolio obtained with sample moments does not consider estimation error at all.

A.2 Minimum-Variance Portfolio

The minimum-variance portfolio reduces the estimation errors by only estimating the variance-covariance matrix. Moreover, Jagannathan and Ma (2003) show that imposing constraints on shortselling is equivalent to "shrinking" the extreme values in the variance-covariance matrix, which they demonstrate leads to a substantial improvement in portfolio performance. The formula for calculating the minimum variance portfolio weights is

$$\min w^{'}\Sigma w \tag{10}$$

$$s.t \;\; 0 \leq w \leq 1 \tag{11}$$

$$\sum_{i=1}^{N} w_i = 1 \tag{12}$$

where w is the matrix of portfolio weights, and Σ is the corresponding variance-covariance matrix. The portfolio weights are constrained to be non-negative and to sum to one. The model only requires estimation of the variance-covariance matrix, which is estimates as in eq.(8).

The optimal portfolio weights are given by

$$w^{MIN} = \frac{1}{\mathbf{1}'(\Sigma^{MV})^{-1}\mathbf{1}} \times (\Sigma^{MV})^{-1}\mathbf{1} \tag{13}$$

A.3 Bayes-Stein Shrinkage Portfolio

The Bayesian approached provides a general framework that integrates estimation risk into the analysis. The Bayes-Stein (BS) portfolio weights are obtained by solving the problem in eq.(4), but where instead of the sample estimates for μ and Σ in eq.(7) and eq.(8), the investor uses shrinkage estimators, defined as a convex combination of the sample mean $\overline{\mu}$ and a global mean. The sample mean is estimated in eq.(7) and the global mean is the mean of the minimum variance portfolio, μ^{MIN}. As in Jorion (1986), the following shrinkage estimators for the expected return and covariance matrix are used:

$$\mu^{BS} = (1-\phi)\mu^{MV} + \phi\mu^{MIN} \tag{14}$$

$$\Sigma^{BS} = \Sigma^{MV}\left(1+\frac{1}{T+\lambda}\right) + \frac{\lambda}{T(T+1+\lambda)}\frac{\mathbf{1}\mathbf{1}'}{\mathbf{1}'\left(\Sigma^{MV}\right)^{-1}\mathbf{1}} \tag{15}$$

where

$$\mu^{MIN} = \frac{\mu^{MV}\left(\Sigma^{MV}\right)^{-1}\mathbf{1}}{\mathbf{1}'\left(\Sigma^{MV}\right)^{-1}\mathbf{1}} \tag{16}$$

$$\phi = \frac{\lambda}{T+\lambda} \tag{17}$$

$$\lambda = \frac{N+2}{\left(\mu^{MV}-\mu^{MIN}\right)'\left(\Sigma^{MV}\right)^{-1}\left(\mu^{MV}-\mu^{MIN}\right)} \tag{18}$$

The optimal portfolio weights are given by

$$w^{BS} = (\Sigma^{BS})^{-1}\mu^{BS} \tag{19}$$

Kan and Zhou (2007) provide an analytical proof to show that the Bayesian portfolio rule always dominates the maximum likelihood estimators as well as the unbiased estimator of Σ^{-1}, by yielding higher expected utility in repeated samples, regardless of the values of the true parameters. Intuitively, this should be the case because the Bayesian portfolio rule incorporates uncertainty into decision-making while the previous models simply ignore it.

A.4 Optimal "Three-Fund" Portfolio

Kan and Zhou (2007) propose a "three-fund" portfolio rule to deal with estimation error. Theoretically, if a mean-variance optimizing investor knows the true parameters, she should invest only in the riskless asset and the tangency portfolio. However, when the parameters are unknown, the tangency portfolio is obtained with estimation error. Including another risky portfolio can help to diversify the estimation risk of the sample tangency portfolio. Kan and Zhou (2007) solve analytically for the the optimal portfolio weights in a three-fund universe that consists of the riskless asset, the sample tangency portfolio, and the sample global minimum-variance portfolio. The global minimum-variance portfolio is used since it only requires estimation of the variance-covariance matrix, which reduces estimation errors. The relative weights in the two risky portfolios depend on the estimation errors of the two portfolios, their correlation, and their risk-return trade-offs.

The optimal three-fund rule in Kan and Zhou (2007) can be thought of as a shrinkage rule with a particular choice of shrinkage estimator of μ and a particular choice of Σ. Hence, the model solves the same problem as in the Bayes-Stein model but with Σ^{III} instead of Σ^{BS} to estimate Σ, so that

$$(\Sigma^{III})^{-1} = \frac{(T-N-1)(T-N-4)}{T(T-2)} \left(\Sigma^{MV}\right)^{-1} \tag{20}$$

and the use of the Bayes-Stein shrinkage estimator μ^{BS}, eq.(7), with the value of

$$\phi = \frac{N}{N + T\psi_a^2} \tag{21}$$

That is,

$$\mu^{III} = \left[\frac{T\psi_a^2}{N + T\psi_a^2}\right] \mu^{MV} + \left[\frac{N}{N + T\psi_a^2}\right] \mu^{MIN}\mathbf{1} \tag{22}$$

where

$$\psi_a^2 = \frac{(T-N-1)\psi^2 - (N-1)}{T} + \frac{2(\psi^2)^{\frac{N-1}{2}}(1+\psi^2)^{-\frac{T-2}{2}}}{TB_{\psi^2/(1+\psi^2)}((N-1)/2, (T-N+1)/2)} \tag{23}$$

$$\psi^2 = (\mu^{MV} - \mu^{MIN})'(\Sigma^{MV})^{-1}(\mu^{MV} - \mu^{MIN}) \tag{24}$$

and where the incomplete Beta function is given by

$$B_x(a,b) = \int_0^x y^{a-1}(1-y)^{b-1}dy \tag{25}$$

The optimal portfolio weights are

$$w^{III} = \left(\Sigma^{III}\right)^{-1} \mu^{III} \tag{26}$$

A.5 Bayesian "Data-and-Model" Portfolio

In a Bayesian framework, informative priors other than the diffuse one may be used. For examples, Pástor (2000) and Pástor and Stambaugh (2000) provide priors that incorporate certain beliefs on the usefulness of the CAPM and study their impacts on asset allocation decisions. Hence, under this "Data-and Model" approach developed in Pástor (2000) and Pástor and Stambaugh (2000), estimation of the moments of asset returns is done using not just the data but also the belief that the asset returns are generated by a particular asset-pricing model. Thus, the Bayesian "Data-and-Model" approach shrinks both the expected returns and the variance-covariance matrix, as demonstrated in Wang (2005).

The model is derived as follows. There are N risky assets and let r_{1t} be the vector of excess returns over the risk-free rate on the assets during period t. The asset pricing model is given and there are K factor portfolios in the model. Let r_{2t} be the vector of excess returns on the factor portfolios during period t. The time series of T observations are assumed to follow a normal distribution with mean μ and variance Ω, independently across t. The mean and variance are decomposed into the following parts corresponding to the N assets and K factors.

$$\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \Omega = \begin{pmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{pmatrix} \tag{27}$$

The mean and variance can be summarized by the parameters in the regression model:

$$r_{1t} = \alpha + \beta r_{2t} + u_t \tag{28}$$

where α is the vector of Jensen's alpha, β is the matrix of the betas, and u_t is the vector of the residual terms in the regression. The variance of u_t is assumed to be Σ. It follows that the mean and variance of the returns can be expressed as

$$\mu = \begin{pmatrix} \alpha + \beta\mu_2 \\ \mu_2 \end{pmatrix}, \Omega = \begin{pmatrix} \beta\Omega_{22}\beta' + \Sigma & \beta\Omega_{22} \\ \Omega_{22}\beta' & \Omega_{22} \end{pmatrix} \tag{29}$$

The asset pricing model, $\mu_1 = \beta\mu_2$, only holds if α is a vector of zeros.

In the classical framework of asset allocation using asset-pricing models, investors choose either to believe or not to believe the asset-pricing model. Those who do not believe the asset-pricing model estimate the parameters without restricting α to be zero. Denote the maximum likelihood estimates of α, β and Σ by $\widehat{\alpha}$, $\widehat{\beta}$ and $\widehat{\Sigma}$ respectively. Similarly, let $\overline{\beta}$ and $\overline{\Sigma}$ be the estimates obtained when estimating the regression model with the restriction that $\alpha = 0$. These would be the estimators chosen by an investor who dogmatically believes in the asset pricing model. The Bayesian framework introduces an informative prior distribution of α to represent an investor's belief in the asset pricing model. The prior of α, conditional on Σ, is assumed to be a normal distribution with mean 0 and variance $\theta\Sigma$, i.e.

$$p(\alpha \mid \Sigma) = N(0, \theta\Sigma) \tag{30}$$

The parameter θ is a positive number that controls the variance of the prior distribution of Jensen's alpha.

Under the assumptions described above, Wang (2005) shows how to obtain estimators for the expected return and variance-covariance matrix that account for the belief of a Bayesian investor over the validity of a particular asset pricing model.

If $\widehat{S}$ denotes the highest Sharpe ratio of the efficient frontier spanned by the mean and variance of the factor portfolios, i.e.

$$\widehat{S}^2 = \widehat{\mu}_2'\widehat{\Omega}_{22}^{-1}\widehat{\mu}_2 \tag{31}$$

and let ω denote the degree of confidence a Bayesian investor places in the asset-pricing model. If $\omega = 1$ then the investor has a dogmatic belief in the model.

$$\omega = \frac{1}{1 + T\theta/(1+\widehat{S}^2)} \tag{32}$$

Then, a Bayesian "Data-and-Model" investor with a degree of confidence ω in the model will use the following shrinkage estimators of the expected return and variance-covariance matrix of the investable assets:

$$\widehat{\mu}^{DM} = \omega \begin{pmatrix} \overline{\beta}\widehat{\mu}_2 \\ \widehat{\mu}_2 \end{pmatrix} + (1-\omega)\begin{pmatrix} \widehat{\mu}_1 \\ \widehat{\mu}_2 \end{pmatrix} \tag{33}$$

$$\widehat{\Omega}^{DM} = \begin{pmatrix} V_{11}(\omega) & V_{12}(\omega) \\ V_{12}(\omega)' & b\widehat{\Omega}_{22} \end{pmatrix} \tag{34}$$

where $V_{11}(\omega)$ and $V_{12}(\omega)$ are given by

$$V_{11}(\omega) = b\left[\omega\overline{\beta} + (1-\omega)\widehat{\beta}\right]\widehat{\Omega}_{22}\left[\omega\overline{\beta} + (1-\omega)\widehat{\beta}\right]' + h\left[\omega\overline{\delta} + (1-\omega)\widehat{\delta}\right]\left[\omega\overline{\Sigma} + (1-\omega)\widehat{\Sigma}\right] \tag{35}$$

$$V_{12}(\omega) = b\left[\omega\overline{\beta} + (1-\omega)\widehat{\beta}\right]\widehat{\Omega}_{22} \tag{36}$$

Here, $\overline{\delta}$, $\widehat{\delta}$, b and h are scalars and defined as follows:

$$\overline{\delta} = \frac{T(T-2)+K}{T(T-K-2)} - \frac{K+3}{T(T-K-2)}\frac{\widehat{S}^2}{(1+\widehat{S}^2)} \tag{37}$$

$$\widehat{\delta} = \frac{(T-2)(T+1)}{T(T-K-2)} \tag{38}$$

$$b = \frac{T+1}{T-K-2} \tag{39}$$

$$h = \frac{T}{T-N-K-1} \tag{40}$$

The mean equation states that the predictive mean is a weighted average of the estimated means restrictive and unrestrictive by the asset-pricing model. It is a shrinkage estimator. The shrinkage target is the maximum likelihood estimate of μ under the restriction of the asset pricing model.

Table I
Strategy Classifications

The table shows the classification of funds into seven broad strategies. The funds are from four different databases (HFR, CISDM, MSCI and TASS) that all have their own classification of hedge fund strategies.

Strategy	Contains funds classified as	
Security Selection	Equity hedge	Equity market neutral
	Equity long-short	
Macro	Macro	Foreign exchange
Relative Value	Relative value	Arbitrage
	Relative value multi-strategy	Capital structure arbitrage
	Relative value arbitrage	Convertible arbitrage
	Other relative value	Statistical arbitrage
	Regulation D	Merger arbitrage
	No bias	Option arbitrage
Directional Traders	Directional trading multi-process	Sector
	Equity long only	Sector: Financial
	Equity non-hedge	Sector: Metals/Mining
	Market timing	Sector: Real estate
	Tactical trading	Sector: Energy
	Systematic trading	Sector: Healthcare/Biotech
	Long bias	Sector: Technology
	Variable bias	Sector: Miscellaneous
Multi Process	Multi-strategy/Multi Process	Private placements
	Event driven	Distressed securities
	Event driven	
Fixed Income	Fixed-income	Fixed-income convertible arbitrage
	Fixed-income arbitrage	Fixed-income high yield
	Fixed-income diversified	Long-short credit
	Fixed-income mortgage-backed	
Other	Discretionary trading	Specialist credit multi-process
	Managed futures	Top-down
	CTA	Bottom-up
	Diversified debt	Value
	Short-selling	Other
	Short bias	No strategy
	Dual approach	

Table II
Summary Statistics

This table presents summary statistics for the seven hedge fund strategies in the sample as well as for equity and long-term bonds. The first panel displays, in rows, the number of funds in the sample, the average life in years, the time series mean of total AUM across all funds in the strategy, the average (value-weighted) performance fee and the percentage of funds that employ lockups. The following panel shows the summary statistics of the monthly returns for the value-weighted hedge fund indices, equity and bonds (in excess over the three-month U.S. Treasury bill). The Jarque-Bera test statistic is distributed as chi-square with 2 degrees of freedom. Asterisk indicates that the hypothesis of normality cannot be rejected at the 5%-level (critical value =5.99).

Panel A: summary Statistics Sample

	Security Selection	Macro	Relative Value	Directional Traders	Multi Process	Fixed Income	Other
Number of funds	1711	796	970	1455	699	399	1157
Average life in years	4.0	4.4	4.4	5.1	4.7	4.3	4.7
Average AUM (US $BN)	60.9	30.7	40.3	51.0	27.5	23.9	27.1
Value-weighted perf. fee (%)	18.6	18.6	19.2	18.7	19.0	16.8	19.3
Funds with lockups (%)	26	5	30	36	33	22	9

Panel B: Summary Statistics Total Returns

	Security Selection	Macro	Relative Value	Directional Traders	Multi Process	Fixed Income	Other	S&P 500	Bond 10y
Mean	0.81	0.79	0.77	0.98	0.92	0.58	0.68	0.71	0.33
Median	0.68	0.60	0.77	0.72	0.96	0.72	0.49	1.02	0.28
Std	2.15	3.18	0.89	2.64	1.42	1.33	2.09	4.14	2.10
Min	-6.80	-7.98	-3.50	-10.26	-7.49	-4.43	-5.02	-14.89	-7.57
Max	8.47	11.11	3.12	8.78	3.76	3.86	6.53	11.06	5.47
Skewness	0.14	0.35	-0.99	-0.15	-1.75	-0.98	0.26	-0.53	-0.42
Kurtosis	2.12	2.05	3.92	2.26	8.52	2.35	0.41	0.85	0.78
JB-stat	4.69*	7.66	26.22	3.51*	234.96	23.45	38.38	31.60	30.99

Table III
Observed Allocation

This table presents the distribution of assets under management (AUM) for the strategies in the sample. The columns represent the strategies, and the rows show the percent of total AUM that is contained within each strategy at the end of each year. The final row gives the averages over the period. The final column presents the total AUM contained across all strategies at the end of each year in billion of US dollars.

Year	Security Selection	Macro	Relative Value	Directional Traders	Multi-Process	Fixed Income	Other	Total U.S. $BN
1994	13%	40%	6%	17%	8%	6%	11%	62.331
1995	14%	34%	7%	23%	9%	6%	11%	78.389
1996	15%	32%	8%	24%	9%	8%	8%	123.548
1997	16%	27%	9%	22%	10%	9%	8%	185.575
1998	23%	23%	11%	23%	10%	11%	9%	211.519
1999	26%	18%	11%	24%	10%	9%	10%	265.548
2000	27%	9%	16%	27%	11%	9%	11%	283.482
2001	31%	5%	20%	22%	11%	10%	11%	337.285
2002	31%	5%	22%	19%	13%	11%	11%	385.106
2003	32%	6%	20%	18%	11%	10%	13%	553.323
2004	30%	6%	19%	18%	15%	10%	14%	717.190
Average	23%	18%	14%	21%	11%	9%	11%	291.209

Table IV
Portfolio Performance 1: Total Returns and Expanding Window

This table shows the performance evaluation metrics; the out-of-sample mean, Sharpe ratio, gain-loss ratio and alpha. In the first row, the table gives the value of the metrics. The second and third rows show the bootstrapped standard errors and the corresponding t-statistic. The standard t-test tests the hypothesis that the metric is equal to zero by using the bootstrapped standard errors. And the fourth row displays the P-values from the testing the difference between the metrics for the naive allocation model and the optimal allocation model. For all metrics, except the Sharpe ratio, a standard test of the difference between two populations is performed using the bootstrapped standard errors. For the Sharpe ratio the Jobson-Korkie test with the correction in Memmel (2003) is used. All strategy indices are value-weighted and the returns are corrected for serial correlation according to Getmansky et al. (2004).

	1/N (rebal)	Mean-var	Min-var	Bayes-Stein	3-fund	Data&Model (omega=0.5)
Performance						
Mean	1.903	1.528	1.451	1.504	1.452	1.450
se_{boot}	0.505	0.255	0.220	0.241	0.233	0.229
t-stat (θ_i= 0)	3.768	5.990	6.602	6.237	6.232	6.328
p-values (θ_i-θ_j= 0)		*0.005*	*0.001*	*0.002*	*0.001*	*0.001*
Sharpe ratio	0.574	0.813	0.926	0.859	0.888	0.861
se_{boot}	0.182	0.228	0.224	0.228	0.227	0.228
t-stat (θ_i= 0)	3.154	3.569	4.137	3.765	3.906	3.779
p-values (θ_i-θ_j= 0)		*0.070*	*0.019*	*0.042*	*0.033*	*0.044*
Gain-loss	2.308	6.167	5.143	6.167	6.167	6.167
se_{boot}	1.631	8.039	8.285	8.146	8.281	8.499
t-stat (θ_i= 0)	1.415	0.767	0.621	0.757	0.745	0.726
p-values (θ_i-θ_j= 0)		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Alphas						
Alpha F&H 7-factor	0.199	0.394	0.380	0.388	0.376	0.344
se_{boot}	0.275	0.130	0.121	0.126	0.123	0.123
t-stat (θ_i= 0)	0.724	3.027	3.151	3.086	3.047	2.802
R-square	0.872	0.794	0.852	0.824	0.848	0.860
p-values (θ_i-θ_j= 0)		*0.045*	*0.059*	*0.050*	*0.066*	*0.133*
Alpha F&H 4-factor	0.183	0.406	0.399	0.404	0.393	0.369
se_{boot}	0.239	0.115	0.103	0.110	0.107	0.106
t-stat (θ_i= 0)	0.766	3.531	3.856	3.675	3.672	3.468
R-square	0.803	0.691	0.769	0.730	0.764	0.783
p-values (θ_i-θ_j= 0)		*0.014*	*0.016*	*0.014*	*0.020*	*0.039*
Alpha FFC 4-factor	0.243	0.436	0.423	0.431	0.419	0.394
se_{boot}	0.223	0.107	0.097	0.102	0.099	0.099
t-stat (θ_i= 0)	1.090	4.066	4.379	4.214	4.212	3.970
R-square	0.787	0.597	0.611	0.606	0.610	0.637
p-values (θ_i-θ_j= 0)		*0.028*	*0.037*	*0.031*	*0.042*	*0.082*

Table V
Portfolio Weights 1: Total Returns and Expanding Window

This table presents results from optimizing over returns on the seven hedge fund strategies and equity (S&P 500) and bonds (U.S. 10-year maturity Treasury bond). All returns are monthly excess returns over the 3-month U.S. Treasury bill corrected for serial correlation as suggested in Getmansky et al. (2004). The portfolio weights are constrained to be between zero and one and sum to one. The optimization is performed using an expanding window and the weights are estimated quarterly during 1994 to 2004. In the table below the mean weight over this period, the standard deviation, the initial and ending weights are indicated in rows for the portfolios. Five optimization models are used, as indicated in columns.

Expanding window: Weights	**Mean-var**	**Min-var**	**Bayes-Stein**	**3-fund**	**Data&Model (omega=0.5)**
Mean					
Security selection	0.00	0.00	0.00	0.00	0.00
Macro	0.02	0.00	0.01	0.00	0.00
Relative value	0.78	0.80	0.79	0.80	0.74
Directional traders	0.00	0.00	0.00	0.00	0.00
Multi process	0.05	0.01	0.03	0.01	0.02
Fixed income	0.03	0.03	0.04	0.03	0.06
Others	0.07	0.05	0.06	0.06	0.05
S&P 500	0.02	0.01	0.02	0.02	0.03
10-year Bond	0.04	0.10	0.06	0.08	0.10
Std					
Security selection	0.00	0.01	0.00	0.01	0.02
Macro	0.02	0.00	0.01	0.01	0.00
Relative value	0.06	0.03	0.04	0.03	0.06
Directional traders	0.00	0.00	0.00	0.00	0.00
Multi process	0.05	0.02	0.04	0.03	0.03
Fixed income	0.05	0.03	0.04	0.03	0.05
Others	0.03	0.01	0.02	0.01	0.02
S&P 500	0.02	0.02	0.02	0.02	0.03
10-year Bond	0.03	0.06	0.05	0.07	0.06
Initial weight					
Security selection	0.00	0.04	0.00	0.03	0.13
Macro	0.07	0.02	0.05	0.02	0.00
Relative value	0.64	0.65	0.64	0.65	0.44
Directional traders	0.00	0.00	0.00	0.00	0.00
Multi process	0.16	0.13	0.15	0.15	0.13
Fixed income	0.07	0.00	0.05	0.00	0.10
Others	0.02	0.00	0.01	0.00	0.00
S&P 500	0.00	0.04	0.01	0.04	0.00
10-year Bond	0.04	0.12	0.08	0.11	0.21
Final weight					
Security selection	0.00	0.00	0.00	0.00	0.00
Macro	0.00	0.00	0.00	0.00	0.00
Relative value	0.78	0.82	0.81	0.83	0.79
Directional traders	0.00	0.00	0.00	0.00	0.00
Multi process	0.08	0.00	0.03	0.00	0.04
Fixed income	0.00	0.00	0.00	0.00	0.00
Others	0.09	0.07	0.08	0.07	0.07
S&P 500	0.00	0.00	0.00	0.00	0.00
10-year Bond	0.05	0.12	0.08	0.09	0.11

Table VI
Portfolio Performance 2: Total Returns and Three-Year Window

This table shows the performance evaluation metrics; the out-of-sample mean, Sharpe ratio, gain-loss ratio and alpha. In the first row, the table gives the value of the metrics. The second and third rows show the bootstrapped standard errors and the corresponding t-statistic. The standard t-test tests the hypothesis that the metric is equal to zero by using the bootstrapped standard errors. And the fourth row displays the P-values from the testing the difference between the metrics for the naive allocation model and the optimal allocation model. For all metrics, except the Sharpe ratio, a standard test of the difference between two populations is performed using the bootstrapped standard errors. For the Sharpe ratio the Jobson-Korkie test with the correction in Memmel (2003) is used. All strategy indices are value-weighted and the returns are corrected for serial correlation according to Getmansky et al. (2004).

	1/N (rebal)	**Mean-var**	**Min-var**	**Bayes-Stein**	**3-fund**	**Data&Model (omega=0.5)**
Performance						
Mean	1.903	1.432	1.404	1.414	1.405	1.409
se_{boot}	0.505	0.257	0.225	0.238	0.227	0.229
t-stat (θ_i= 0)	3.768	5.565	6.243	5.932	6.191	6.143
p-values (θ_i-θ_j= 0)		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Sharpe ratio	0.574	0.800	0.835	0.815	0.834	0.808
se_{boot}	0.182	0.227	0.227	0.228	0.227	0.229
t-stat (θ_i= 0)	3.154	3.529	3.675	3.570	3.679	3.531
p-values (θ_i-θ_j= 0)		*0.135*	*0.115*	*0.127*	*0.115*	*0.151*
Gain-loss	2.308	5.143	5.143	5.143	5.143	5.143
se_{boot}	1.631	7.476	7.856	8.264	7.435	7.837
t-stat (θ_i= 0)	1.415	0.688	0.655	0.622	0.692	0.656
p-values (θ_i-θ_j= 0)		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Alphas						
Alpha F&H 7-factor	0.199	0.399	0.404	0.400	0.404	0.380
se_{boot}	0.275	0.135	0.123	0.128	0.125	0.125
t-stat (θ_i= 0)	0.724	2.959	3.271	3.125	3.243	3.042
R-square	0.872	0.794	0.824	0.803	0.819	0.854
p-values (θ_i-θ_j= 0)		*0.041*	*0.034*	*0.038*	*0.033*	*0.061*
Alpha F&H 4-factor	0.183	0.393	0.403	0.397	0.403	0.379
se_{boot}	0.239	0.120	0.106	0.112	0.108	0.108
t-stat (θ_i= 0)	0.766	3.270	3.797	3.533	3.748	3.508
R-square	0.803	0.674	0.721	0.688	0.712	0.766
p-values (θ_i-θ_j= 0)		*0.022*	*0.014*	*0.018*	*0.014*	*0.030*
Alpha FFC 4-factor	0.243	0.413	0.415	0.416	0.415	0.400
se_{boot}	0.223	0.112	0.099	0.104	0.100	0.101
t-stat (θ_i= 0)	1.090	3.689	4.187	3.993	4.155	3.972
R-square	0.787	0.551	0.567	0.554	0.562	0.600
p-values (θ_i-θ_j= 0)		*0.054*	*0.047*	*0.048*	*0.047*	*0.070*

Table VII
Portfolio Weights 2: Total Returns and Three-Year Window

This table presents results from optimizing over returns on the seven hedge fund strategies and equity (S&P 500) and bonds (U.S. 10-year maturity Treasury bond). All returns are monthly excess returns over the 3-month U.S. Treasury bill corrected for serial correlation as suggested in Getmansky et al. (2004). The portfolio weights are constrained to be between zero and one and sum to one. The optimization is performed using a three-year window and the weights are estimated quarterly during 1994 to 2004. In the table below the mean weight over this period, the standard deviation, the initial and ending weights are indicated in rows for the portfolios. Five optimization models are used, as indicated in columns.

	Mean-var	**Min-var**	**Bayes-Stein**	**3-fund**	**Data&Model (omega=0.5)**
Mean					
Security selection	0.00	0.01	0.00	0.01	0.01
Macro	0.00	0.00	0.00	0.00	0.00
Relative value	0.75	0.72	0.75	0.73	0.68
Directional traders	0.00	0.00	0.00	0.00	0.00
Multi process	0.03	0.01	0.02	0.01	0.02
Fixed income	0.01	0.05	0.03	0.04	0.04
Others	0.09	0.07	0.08	0.07	0.06
S&P 500	0.02	0.01	0.01	0.01	0.03
10-year Bond	0.09	0.13	0.11	0.13	0.16
Std					
Security selection	0.00	0.04	0.01	0.04	0.04
Macro	0.01	0.01	0.01	0.01	0.01
Relative value	0.12	0.09	0.12	0.10	0.10
Directional traders	0.00	0.00	0.00	0.00	0.00
Multi process	0.05	0.03	0.05	0.04	0.04
Fixed income	0.04	0.07	0.05	0.06	0.07
Others	0.06	0.05	0.06	0.05	0.05
S&P 500	0.03	0.02	0.03	0.02	0.05
10-year Bond	0.09	0.11	0.10	0.11	0.12
Initial weight					
Security selection	0.00	0.00	0.00	0.00	0.09
Macro	0.05	0.01	0.03	0.02	0.00
Relative value	0.61	0.62	0.61	0.61	0.42
Directional traders	0.00	0.00	0.00	0.00	0.00
Multi process	0.18	0.15	0.18	0.16	0.15
Fixed income	0.06	0.00	0.03	0.00	0.08
Others	0.01	0.00	0.00	0.00	0.00
S&P 500	0.00	0.06	0.03	0.06	0.02
10-year Bond	0.09	0.16	0.11	0.15	0.25
Final weight					
Security selection	0.00	0.11	0.00	0.10	0.11
Macro	0.05	0.04	0.05	0.05	0.09
Relative value	0.86	0.80	0.88	0.81	0.72
Directional traders	0.00	0.00	0.00	0.00	0.00
Multi process	0.05	0.00	0.03	0.00	0.01
Fixed income	0.00	0.00	0.00	0.00	0.00
Others	0.00	0.00	0.00	0.00	0.00
S&P 500	0.00	0.00	0.00	0.00	0.00
10-year Bond	0.04	0.05	0.04	0.05	0.07

Table VIII
Portfolio Performance 3:
Non-Systematic Returns and Expanding Window

This table shows the performance evaluation metrics, the out-of-sample mean, Sharpe ratio, gain-loss ratio and alpha when optimizing over non-systematic returns. The non-systematic returns are constructed by subtracting the sum of coefficients from the Fung and Hsieh (2004) regression times the factor returns from the total returns. In the first row, the table gives the value of the metrics. The second and third rows show the bootstrapped standard errors and the corresponding t-statistic. The standard t-test tests the hypothesis that the metric is equal to zero by using the bootstrapped standard errors. And the fourth row displays the P-values from the testing the difference between the metrics for the naive allocation model and the optimal allocation model. For all metrics, except the Sharpe ratio, a standard test of the difference between two populations is performed using the bootstrapped standard errors. For the Sharpe ratio the Jobson-Korkie test with the correction in Memmel (2003) is used. All strategy indices are value-weighted and the returns are corrected for serial correlation according to Getmansky et al. (2004).

	1/N (rebal)	Mean-var	Min-var	Bayes-Stein	3-fund
Performance					
Mean	1.903	1.668	1.556	1.638	1.569
se_{boot}	0.505	0.254	0.209	0.239	0.228
t-stat (θ_i= 0)	3.768	6.572	7.436	6.848	6.872
p-values (θ_i-θ_j= 0)		*0.061*	*0.004*	*0.033*	*0.007*
Sharpe ratio	0.574	0.832	0.771	0.822	0.795
se_{boot}	0.182	0.255	0.246	0.254	0.251
t-stat (θ_i= 0)	3.154	3.267	3.140	3.242	3.171
p-values (θ_i-θ_j= 0)		*0.007*	*0.021*	*0.008*	*0.015*
Gain-loss	2.308	3.300	3.778	3.778	4.375
se_{boot}	1.631	11.097	11.561	11.130	11.416
t-stat (θ_i= 0)	1.415	0.297	0.327	0.339	0.383
p-values (θ_i-θ_j= 0)		*0.200*	*0.036*	*0.033*	*0.002*
Alphas					
Alpha F&H 7-factor	0.199	0.765	0.698	0.752	0.713
se_{boot}	0.275	0.137	0.119	0.130	0.125
t-stat (θ_i= 0)	0.724	5.595	5.889	5.782	5.683
R-square	0.872	0.605	0.596	0.595	0.595
p-values (θ_i-θ_j= 0)		*0.012*	*0.001*	*0.007*	*0.002*

Table IX

Portfolio Weights 3: Non-Systematic Returns and Expanding Window

This table presents results from optimizing over non-systematic returns on the seven hedge fund strategies and equity (S&P 500) and bonds (U.S. 10-year maturity Treasury bond). The non-systematic returns are constructed by subtracting the sum of coefficients from the Fung and Hsieh (2004) regression times the factor returns from the total returns. All returns are monthly excess returns over the 3-month U.S. Treasury bill corrected for serial correlation as suggested in Getmansky et al. (2004). The portfolio weights are constrained to be between zero and one and sum to one. The optimization is performed using an expanding window and the weights are estimated quarterly during 1994 to 2004. In the table below the mean weight over this period, the standard deviation, the inital and ending weights are indicated in rows for the portfolios. Four optimization models are used, as indicated in columns.

	Mean-var	**Min-var**	**Bayes-Stein**	**3-fund**
Mean				
Security selection	0.02	0.20	0.05	0.07
Macro	0.04	0.00	0.03	0.02
Relative value	0.75	0.48	0.72	0.67
Directional traders	0.00	0.00	0.00	0.00
Multi process	0.04	0.00	0.03	0.02
Fixed income	0.01	0.19	0.03	0.08
Others	0.08	0.04	0.07	0.06
S&P 500	0.05	0.01	0.04	0.03
10-year Bond	0.01	0.07	0.03	0.04
Std				
Security selection	0.03	0.08	0.05	0.06
Macro	0.04	0.00	0.04	0.02
Relative value	0.04	0.06	0.07	0.09
Directional traders	0.00	0.00	0.00	0.00
Multi process	0.05	0.01	0.04	0.03
Fixed income	0.02	0.03	0.04	0.05
Others	0.02	0.01	0.01	0.01
S&P 500	0.02	0.00	0.02	0.01
10-year Bond	0.02	0.01	0.03	0.03
Initial weight				
Security selection	0.00	0.33	0.00	0.09
Macro	0.12	0.00	0.11	0.05
Relative value	0.78	0.40	0.76	0.66
Directional traders	0.00	0.00	0.00	0.00
Multi process	0.00	0.00	0.03	0.09
Fixed income	0.00	0.18	0.00	0.01
Others	0.08	0.02	0.06	0.03
S&P 500	0.02	0.01	0.02	0.02
10-year Bond	0.00	0.06	0.02	0.05
Final weight				
Security selection	0.00	0.06	0.02	0.03
Macro	0.00	0.00	0.00	0.00
Relative value	0.69	0.58	0.70	0.68
Directional traders	0.00	0.00	0.00	0.00
Multi process	0.15	0.02	0.12	0.09
Fixed income	0.00	0.18	0.00	0.03
Others	0.09	0.06	0.08	0.07
S&P 500	0.03	0.02	0.03	0.03
10-year Bond	0.04	0.08	0.06	0.06

Table X
Portfolio Performance 4:
Non-Systematic Returns and Expanding Window

This table shows the performance evaluation metrics, the out-of-sample mean, Sharpe ratio, gain-loss ratio and alpha when optimizing over non-systematic returns. The non-systematic returns are constructed by subtracting the sum of coefficients from the Fung and Hsieh (2004) regression times the factor returns from the total returns. In the first row, the table gives the value of the metrics. The second and third rows show the bootstrapped standard errors and the corresponding t-statistic. The standard t-test tests the hypothesis that the metric is equal to zero by using the bootstrapped standard errors. And the fourth row displays the P-values from the testing the difference between the metrics for the naive allocation model and the optimal allocation model. For all metrics, except the Sharpe ratio, a standard test of the difference between two populations is performed using the bootstrapped standard errors. For the Sharpe ratio the Jobson-Korkie test with the correction in Memmel (2003) is used. All strategy indices are value-weighted and the returns are corrected for serial correlation according to Getmansky et al. (2004).

	1/N (rebal)	**Mean-var**	**Min-var**	**Bayes-Stein**	**3-fund**
Performance					
Mean	1.903	1.732	1.518	1.677	1.602
se_{boot}	0.505	0.274	0.207	0.244	0.214
t-stat (θ_i= 0)	3.768	6.323	7.330	6.882	7.483
p-values (θ_i-θ_j= 0)		*0.178*	*0.002*	*0.070*	*0.014*
Sharpe ratio	0.574	0.789	0.771	0.807	0.811
se_{boot}	0.182	0.231	0.243	0.238	0.243
t-stat (θ_i= 0)	3.154	3.411	3.178	3.394	3.334
p-values (θ_i-θ_j= 0)		*0.041*	*0.112*	*0.038*	*0.061*
Gain-loss	2.308	3.778	4.375	5.143	5.143
se_{boot}	1.631	8.828	10.256	9.470	10.194
t-stat (θ_i= 0)	1.415	0.428	0.427	0.543	0.505
p-values (θ_i-θ_j= 0)		*0.018*	*0.001*	*0.001*	*0.000*
Alphas					
Alpha F&H 7-factor	0.199	0.447	0.429	0.458	0.451
se_{boot}	0.275	0.102	0.109	0.124	0.111
t-stat (θ_i= 0)	0.724	4.393	3.926	3.651	4.064
R-square	0.872	0.828	0.826	0.821	0.803
p-values (θ_i-θ_j= 0)		*0.019*	*0.000*	*0.003*	*0.000*

Table XI

Portfolio Weights 4: Non-Systematic Returns and Three-Year Window

This table presents results from optimizing over non-systematic returns on the seven hedge fund strategies and equity (S&P 500) and bonds (U.S. 10-year maturity Treasury bond). T The non-systematic returns are constructed by subtracting the sum of coefficients from the Fung and Hsieh (2004) regression times the factor returns from the total returns. All returns are monthly excess returns over the 3-month U.S. Treasury bill corrected for serial correlation as suggested in Getmansky et al. (2004). The portfolio weights are constrained to be between zero and one and sum to one. The optimization is performed using a three-year window and the weights are estimated quarterly during 1994 to 2004. In the table below the mean weight over this period, the standard deviation, the inital and ending weights are indicated in rows for the portfolios. Four optimization models are used, as indicated in columns.

	Mean-var	**Min-var**	**Bayes-Stein**	**3-fund**
Mean				
Security selection	0.04	0.09	0.03	0.04
Macro	0.02	0.01	0.01	0.01
Relative value	0.68	0.59	0.73	0.71
Directional traders	0.02	0.01	0.02	0.02
Multi process	0.07	0.05	0.07	0.06
Fixed income	0.00	0.13	0.00	0.04
Others	0.09	0.06	0.08	0.07
S&P 500	0.04	0.01	0.03	0.02
10-year Bond	0.04	0.05	0.02	0.03
Std				
Security selection	0.09	0.11	0.07	0.06
Macro	0.03	0.04	0.03	0.03
Relative value	0.13	0.16	0.11	0.12
Directional traders	0.06	0.03	0.05	0.03
Multi process	0.10	0.08	0.09	0.08
Fixed income	0.00	0.13	0.01	0.06
Others	0.08	0.05	0.07	0.05
S&P 500	0.04	0.01	0.03	0.01
10-year Bond	0.02	0.02	0.02	0.02
Initial weight				
Security selection	0.00	0.33	0.00	0.09
Macro	0.12	0.00	0.11	0.05
Relative value	0.78	0.40	0.76	0.66
Directional traders	0.00	0.00	0.00	0.00
Multi process	0.00	0.00	0.03	0.09
Fixed income	0.00	0.18	0.00	0.01
Others	0.08	0.02	0.06	0.03
S&P 500	0.02	0.01	0.02	0.02
10-year Bond	0.00	0.06	0.02	0.05
Final weight				
Security selection	0.00	0.18	0.00	0.17
Macro	0.00	0.22	0.12	0.20
Relative value	0.88	0.42	0.80	0.49
Directional traders	0.00	0.00	0.00	0.00
Multi process	0.07	0.00	0.04	0.00
Fixed income	0.00	0.15	0.00	0.10
Others	0.00	0.00	0.00	0.00
S&P 500	0.01	0.01	0.01	0.01
10-year Bond	0.04	0.02	0.03	0.03

Figure 1
Cumulative Total Strategy Returns

This figure plots the cumulative total value-weighted return indices of the seven hedge fund strategies as well as the S&P 500 index (SNP) and the U.S. 10-year maturity Treasury bond (BD10y). The hedge fund strategies are the following: Security Selection (SS), Macro (M), Relative Value (RV), Directional Traders (DT), Multi Process (MP), Fixed Income (FI) and Other (O). The data begin in the first month of 1994 and end in the final month of 2004.

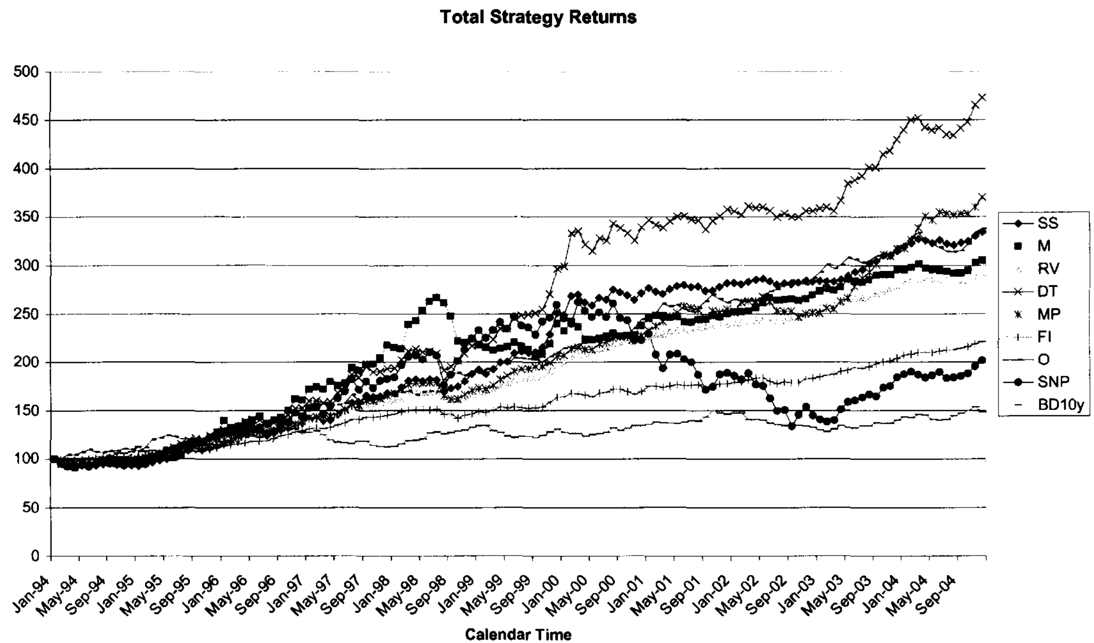


Figure 2
Cumulative Risk-Adjusted Returns Strategies

This figure plots the cumulative risk-adjusted value-weighted return indices of the seven hedge fund strategies: Security Selection (SS), Macro (M), Relative Value (RV), Directional Traders (DT), Multi Process (MP), Fixed Income (FI) and Other (O). The data begin in the first month of 1994 and end in the final month of 2004.

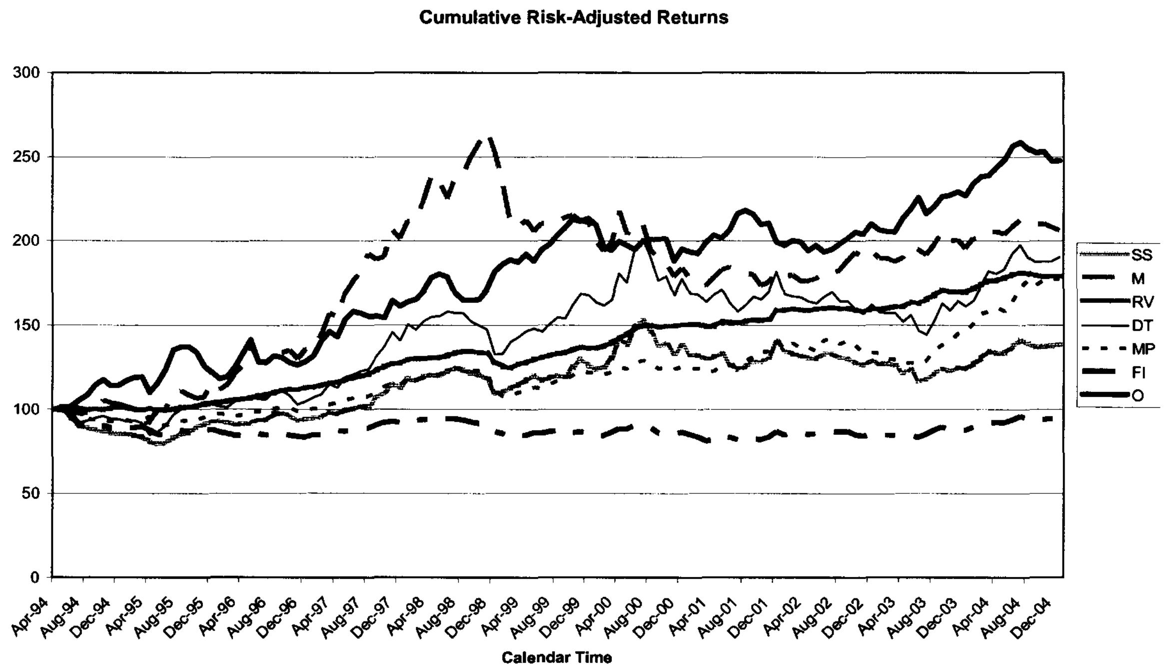
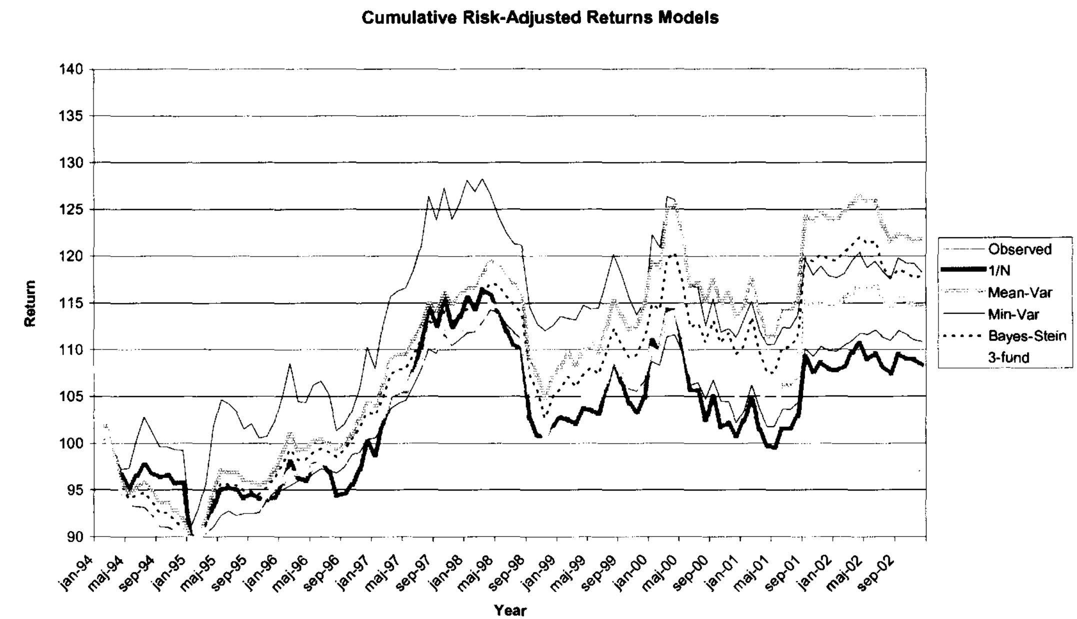


Figure 3
Cumulative Risk-Adjusted Returns Models

This figure plots the cumulative risk-adjusted returns of five optimal allocation models (Mean-variance, Minimum-variance, Bayes-Stein and Optimal 3-fund portfolio and Data-and-Model) and the naive allocation model with rebalancing (1/N). The graph is based on the resulting return series from optimizing over non-systematic returns using an expanding window. Moreover, the graph displays the observed hedge fund portfolio allocation, proxied by the distribution of assets under management between strategies in the sample. The data begin in the first month of 1994 and end in the final month of 2004.



I Appendix: Hedge Fund Strategy Definitions

This appendix aims to give a definition of the most common broad hedge fund strategies. Given the diversity in hedge fund strategies, the list is not intended to be exhaustive.

I.1 Security Selection

Security Selection funds combine long and short positions (mainly in equity) in order to benefit from the manager's ability to select investments while trying to avoid having a large exposure to market risks. The idea is to identify undervalued or overvalued assets and to invest in these assets before the market reacts to the mispricing.

Examples of sub-groups within the Security Selection strategy are Equity hedge and Equity market neutral (also called Equity long/short). Equity hedge funds invest long in equities but tend to hedge those positions with short sales of stocks and/or stock index options. Equity market neutral funds exploit pricing inefficiencies between related equity securities and neutralize exposure to market risk by combining long and short positions.

I.2 Directional Trading

Directional Trading strategies are based upon speculating on the direction of market prices of currencies, commodities, equities and bonds. The strategy Discretionary traders attempts to opportunistically take advantage of price changes of the market or security in which they trade, regardless of what is driving the price action. Their positions are generally unhedged.

Examples of Directional Trading strategies are Market timing, Equity non-hedge and Sector funds. Market Timing involves allocating assets among investments by switching into investments that appear to be beginning an uptrend, and switching out of investments that appear to be starting a downtrend. Equity Non-Hedge funds are mainly long equities and, unlike Equity hedge funds, they do not always hedge their positions. Sector funds focus on investment within a specific sector, such as for example the energy sector or healthcare/biotechnology sector.

I.3 Relative Value

Relative Value strategies use arbitrage techniques to take advantage of spread relationships between prices of financial assets or commodities. The rationale for arbitrage trades is that the price will eventually converge to a known, theoretical or equilibrium price. Returns are generated from elimination the pricing anomalies. Typically spreads are narrow and returns are marginal, hence, leverage is often used to amplify the returns. Managers aim for market neutrality and actively hedge risks using a variety of instruments.

One example of an arbitrage based strategy is Convertible arbitrage, which involves purchasing a portfolio of convertible securities, generally convertible bonds, and hedging the equity risk by selling short the underlying common stock. This strategy is employed in situations in which the manager anticipates the convertible bond to be more valuable than its current market price.

Another example is Merger arbitrages, which attempts to capture the price spread between current market prices of securities and their value after successful completion of a takeover, merger or restructuring. In mergers involving an offer of stock in the acquiring company, the spread is the difference between the current values of the target company stock and the acquiring company stock. Capturing this spread typically involves buying the stock of the target company and shorting an appropriate amount of the acquiring company's stock.

An finally, Statistical arbitrage utilizes quantitative analysis of technical factors to exploit pricing inefficiencies between related equity securities, neutralizing exposure to market risk by combining long and short positions.

I.4 Multi-Process

The Multi-Process strategy comprises funds, which have an investment strategy involving several different investment processes. Examples are Distressed securities, Private placements, Event driven and Specialist credit. Distressed securities seek to invest in companies suffering financial distress. Private Placement funds make short-term private placements in listed companies. In the United States markets the private placement is primarily implemented through Regulation D. Event-Driven encompasses a combination of investment processes targeting securities which experience a change in valuation due to corporate transactions. For instance, a strategy focusing on acquisitions and bankruptcies combines elements of two investment processes: Merger arbitrage and Distressed securities. Specialist Credit seeks to lend to credit-sensitive (generally below investment-grade) issuers. Positive returns are generated from the manager's ability to perform a high level of due diligence and to take advantage of relatively inexpensive securities. The securities may be inexpensive due to regulatory anomalies or other constraints on traditional lenders (e.g., speed of decision-making process, disclosure rules).

I.5 Macro

Macro involves investing by making leveraged bets on anticipated price movements of stock markets, interest rates, foreign exchange and commodities. Macro funds can invest in any markets using any instruments to participate in expected market movements. These movements may result from forecasted shifts in world economies, political fortunes or global supply and demand for resources.

I.6 Emerging Markets

Emerging Markets funds invest in securities of companies or the sovereign debt of developing countries. Investments are primarily long. Emerging Markets include countries in Latin America, Eastern Europe, the former Soviet Union, Africa and parts of Asia. Global emerging market funds will shift their weightings among these regions according to market conditions and manager perspectives. Moreover, some managers only invest in individual regions.

I.7 Fund-of-Funds

Fund-of-funds invest in multiple hedge funds to create a diversified portfolio. The purpose is to reduce the risk of investing with an individual manager. The fund-of-funds manager can choose which strategies and funds to invest in for the portfolio. The advantage for the investor is that the minimum investment in a fund-of-funds may be lower than an investment in an individual hedge fund. The disadvantage is the extra fee that should be paid to the fund-of-funds manager.

I.8 Fixed Income

The common factor for Fixed Income funds is that they all base their trading strategy on fixed income instruments. There is then a variety of sub-strategies within the Fixed Income strategy. Some funds have an arbitrage strategy, exploiting pricing inefficiencies between related fixed income securities while neutralizing exposure to interest rate risk. Others trade in convertible bonds, non-investment grade debt or mortgage-backed securities.

I.9 CTAs

Commodity trading advisors (CTAs), which are also called Managed Futures, manage client assets on a discretionary basis, using global futures markets. Typical areas of focus include metals, grains, equity indexes and soft commodities (cotton, cocoa, coffee, sugar), as well as foreign currency and U.S. government bond futures.

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