Has Hedge Fund Alpha Disappeared?*

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Current Draft: May 2009

Abstract

This paper investigates the alpha generation of the hedge fund industry based on a recent sample compiled from the Lipper/TASS database covering the time period from January 1994 to September 2008. We find a positive average hedge fund alpha in the cross-section for the majority of strategies and a positive and significant alpha for roughly half of all funds. Moreover, the alpha of three-quarter of the strategy indices is positive and significant in the time series. A comparison of a factor model in which the risk factors are selected based on a stepwise regression approach and the widely used factor model proposed by Fung and Hsieh (2004) reveals that the estimated alpha is robust with respect to the choice of the factor model. In contrast to prior research, we find no evidence of a decreasing hedge fund alpha over time. Moreover, based on our sample, we cannot confirm prior evidence pointing to capacity constraints in the hedge fund industry.

JEL Classification: G23
Keywords: Hedge Funds; Performance; Alpha; Factor Models; Capacity Constraints

*We thank the participants of the joint research workshop of the University of St. Gallen and the University of Constance for their valuable comments.

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1 Introduction

This paper investigates hedge fund alpha based on alternative return-based benchmark models. In line with the existing literature, we are able to identify a positive alpha for all strategies in the time series and in the cross-section. However, our analysis challenges the conclusion of some recent research on a decreasing alpha over time (e.g., Fung et al., 2008; Zhong, 2008) and on capacity constraints in the hedge fund industry (e.g., Naik et al., 2007; Fung et al., 2008).

The amount of capital invested in the hedge fund industry increased significantly during the period 1994 to 2008.[1] An expected consequence of this development is a decrease in hedge fund alpha. As new money flows into the hedge fund industry, managers might be forced not only to invest into the most profitable strategies but to opt for less attractive investments or diversify to other strategies, where their knowledge and experience might be limited. Additionally, there might be only a limited dollar amount of alpha in the market, which would then have to be shared among more hedge funds.

The majority of research conducted on hedge fund performance finds that hedge funds on average outperform passive benchmarks (e.g., Agarwal and Naik, 2000; Fung and Hsieh, 2004; Hasanhodzic and Lo, 2007; Kosowski et al., 2007; Amenc et al., 2008; Titman and Tiu, 2008). However, some recent studies suggest that hedge fund alpha has been decreasing over time. Investigating a merged dataset from the three hedge fund databases TASS, HFR, and CISDM, Fung et al. (2008) find that the alpha generated by an index of funds of hedge funds has significantly declined during the period April 2000 to December 2004. As they observe increasing capital inflows into the industry over time, they conclude that the declining alpha could be due to decreasing returns to scale caused by capacity constraints. They argue that their results are consistent with Berk and Green's (2004) rational model of active portfolio management, which states that in an economy with competitive provision of capital and rational investors differential managerial ability will be reflected in the fees charged and

[1] According to the TASS Asset Flow Report of Q4 2008, it increased in this period from USD 50bn to USD 1,209bn at the end of the fourth quarter, with a peak of 1,550bn at the end of Q2 2008.

hence risk-adjusted returns in equilibrium will be zero. Fung et al. (2008) show that funds, which are able to deliver alpha, experience far greater capital inflows than their less successful peers and they demonstrate that these capital flows adversely affect the future risk-adjusted performance of funds. Naik et al. (2007) address the same question at the level of hedge fund strategies. Based on self-constructed value-weighted and equally-weighted strategy indices their results suggest that alpha in equilibrium will be zero as proposed by Berk and Green (2004).

Zhong (2008) conducts a time series analysis of the distribution of single hedge fund alphas based on the seven-factor model of Fung and Hsieh (2004) and finds that not only the average alpha has decreased, but also the number of funds generating a positive alpha. The paper also investigates the relationship between fund flows and performance. Zhong (2008) concludes that on a fund level capital flows have a positive (negative) impact on a fund's future performance for smaller (larger) funds. Hence, he confirms the findings of Naik et al. (2007) that fund flows at a strategy level increase the competition within the strategy and exert pressure on the future performance.

In this paper, we contribute to the existing literature by investigating hedge fund alpha based on a recent and comprehensive data set compiled from Lipper/TASS while accounting for dynamics and nonlinearities in the factor exposures. Specifically, we establish a factor model, in which we select the risk factors based on a stepwise regression approach, and compare the results to the widely used factor model proposed by Fung and Hsieh (2004). In the factor model based on stepwise regression, we account for the possible non-linearity of hedge fund returns by including option-based return factors and lookback straddles in the set of potential risk factors. By estimating the factor exposures based on rolling-window regressions, we apply these factor models as a dynamic benchmark for the returns of equally-weighted and value-weighted hedge fund strategy indices and single hedge funds.

In line with recent research, we find that hedge fund alpha has been positive most of the time for both factor models. However, our results challenge some of the findings in earlier research. Most importantly, we cannot confirm a systematic decrease of the alpha over time.

The only strategy for which we report a steadily decreasing alpha over time is Dedicated Short Bias, although its alpha has picked up again since summer 2007. Furthermore, based on our recent sample of hedge fund returns, we do not find a negative relationship between fund flows and alpha. Hence, we cannot empirically confirm the existence of capacity constraints in the hedge fund industry.

The paper proceeds as follows. Section 2 describes the underlying data set. Section 3 describes the methodology applied for the analysis at hand. Section 4 summarizes the results of the analysis and Section 5 concludes.

2 Data

We use the Lipper/TASS database covering the period from January 1994 to September 2008. As opposed to mutual funds, hedge funds are not required to publicly disclose their returns. Consequently, the returns from all hedge fund databases contain some biases, such as the selection or backfill bias. For a detailed discussion of these biases, the reader may refer to Fung and Hsieh (2000), Fung and Hsieh (2004), or Titman and Tiu (2008).

In our dataset, the survivorship bias is minimized by including live and dead funds in the sample and restricting the sample period to the post-1993 period, when TASS started to keep all hedge funds which stopped reporting in their graveyard database. We control for the backfilling bias (or instant history bias) by deleting all backfilled entries which were added to the database before a fund started reporting to the database. This date is known for roughly 95% of all funds in our sample. For the remaining 5% we follow common practice and delete the first 12 return observations (e.g., Fung and Hsieh, 2000; Edwards and Caglayan, 2001).

As we estimate alpha based on rolling 24-month window regression, we require at least 24 non-backfilled return observations for a fund to be included in our analysis. This requirement may introduce a sampling bias. However, Fung and Hsieh (2000) investigate this bias, which they call multi-period sampling bias, by comparing the average returns of all funds in the sample to the average returns of the funds with at least a 24 months history of returns, and find it to be very small. Furthermore, we only include hedge funds reporting in USD and funds reporting their assets under management. For funds to be included in the equally-weighted strategy index, we additionally require their assets under management to exceed USD 5 millions at least once during their non-backfilled observations. After all these adjustments, we are left with a sample of 3,491 hedge funds for all analyses conducted on the equally-weighted index and 3,738 funds for all analyses conducted on the value-weighted index, where the 5 million assets under management requirement is not imposed. The sample used for the analysis at hand includes roughly half of the funds that reported to TASS and amounts to assets under management of USD 530 billion at the end of August 2008.

The illiquidity of some of the markets in which the hedge funds are invested might have an influence on the reported returns. Driven by the fact that hedge funds avail the possibility to invest in highly illiquid assets without daily market prices and by the fact that the reported returns are only audited on an annual basis, Agarwal and Naik (2000) point out that some intra-year persistence may be caused by stale prices. In order to adjust for the bias of these stale valuations, the return series of our sample are desmoothed as suggested by Getmansky et al. (2004).[2]

Getmansky et al. (2004) demonstrate that instead of the (serially uncorrelated) true returns of a fund (R_t), we only observe reported returns of the funds (R_t^o), which feature the following relationship with actual returns:

$$R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \cdots + \theta_k R_{t-k} \tag{1}$$

$$\text{with} \quad \theta_j \in [0,1], \qquad j = 0, \ldots, k \tag{2}$$

$$\text{and} \quad 1 = \theta_0 + \theta_1 + \cdots + \theta_k \tag{3}$$

In this paper we set k equal to two and estimate θ_0, θ_1, and θ_2 for each hedge fund strategy by estimating this MA(2) model with maximum likelihood.[3] We use these thetas

[2] Jagannathan et al. (2009) find that this procedure of desmoothing the returns leads to a reduction of hedge fund alpha.

[3] As Getmansky et al. (2004), we use a standard MA(k) estimation package (Stata) and transform the resulting

to obtain desmoothed returns which are then included as dependent variables in our multi-factor models. The estimated values for θ_0, θ_1, and θ_2 in Table 1 show that as expected hedge fund styles investing in illiquid assets display higher autocorrelations in their returns (e.g., Convertible Arbitrage, Event Driven, and Fund of Funds) than strategies investing in more liquid assets (e.g., Managed Futures, Equity Market Neutral, Global Macro).

3 Methodology

While there is an extensive literature on hedge fund performance measurement, there is no consensus so far on which factors to include in a multi-factor model. In an attempt to capture the different investment styles and to minimize the risk of omitted risk factors, we use a systematic procedure to select relevant factors among those frequently used in prior literature. Due to limits of degrees of freedom in estimating the model, we attempt to keep the amount of factors included in the factor model as low as possible, while still being able to describe the investment opportunities available to hedge funds as appropriately as possible. We follow Agarwal and Naik (2004) and Titman and Tiu (2008) and use stepwise regressions for the selection of the risk factors to be included in our factor models. For the selection procedure we start with 23 risk factors. We then regress the returns of an equally-weighted index of all funds within a strategy in our sample on the returns of these factors. The stepwise regression approach is based on the t-values of the slope coefficients over the entire sample period with constant coefficients. A factor is added to the model when its marginal significance exceeds the 95% level. We drop any previously chosen factor which is not simultaneously significant with all other factors at least on a 90% confidence level. This iterative procedure is continued until a maximum of seven factors for each hedge fund strategy is obtained or no more significant factors can be identified. We employ the identical risk factors for all funds within a strategy.

To estimate hedge fund alpha based on a factor model, most papers use either zero in-

estimates by dividing each theta by $1 + \theta_1 + \theta_2$ to satisfy Equation (3). In contrast, and also consistent with Getmansky et al. (2004), we do not impose Equation (2) when estimating the thetas and use this restriction as a specification test.

vestment factors or excess returns of buy and hold factors above the risk free rate.[4] The factors we consider include fungible factors of the following asset classes: equities, bonds and credit, interest rates, currencies, options, volatility, dynamic trading strategies, commodities, real estate, and convertible bonds. Most of these factors are excess returns above the risk free rate; some are zero-investment portfolios. We account for the possibility of non-linear factor exposures of hedge funds by including option-based factors in our factor models. These include the returns of the dynamic trading strategies (based on lookback option straddles) proposed by Fung and Hsieh (2001) and the return of European ATM call and put options on the S&P 500 index as suggested by Agarwal and Naik (2004). Unlike Agarwal and Naik (2004), who use ATM options and 1% OTM options, we include ATM options and 7.5% OTM options. We use further out-of-the money options in an attempt to capture the possibility of hedge funds to sell tail risk and not to include too higly correlated risk factors in our model. The complete set of factors considered for the selection procedure is listed in Appendix A. The choice of factors resulting from the stepwise procedure for each strategy is reported in Table 2.

We compare the results of these factor models obtained by stepwise regressions with those from the widely used seven-factor model of Fung and Hsieh (2004). Titman and Tiu (2008), for example, show the alpha from their stepwise approach to be lower than that resulting from the seven-factor model and the r-squares to be significantly higher. The seven factors proposed by Fung and Hsieh (2004) include three trend-following risk factors on bonds, currencies, and commodities, two equity-oriented risk factors (the S&P 500 monthly total return and a size spread factor—either the Wilshire Small Cap 1750 minus Wilshire Large Cap 750 monthly return or Russel 2000 TR minus S&P 500 TR), and two bond-oriented risk factors (the monthly change in the 10-year treasury constant maturity yield and the monthly change in spread between the Moody's Baa yield less the 10-year treasury constant maturity yield). The changes in spreads are both first differences of the levels.

[4]Such papers include Fama and French (1993), Carhart (1997), Edwards and Caglayan (2001), Ennis and Sebastian (2003), Agarwal and Naik (2004), Capocci and Hübner (2004), Ammann and Moerth (2008), Titman and Tiu (2008).

We apply two different approaches to estimate the factor loadings and alphas. First, we run standard ordinary least squares regressions with constant factor loadings over the full sample period as well as for several subperiods. Second, to account for the non-discrete dynamics in the exposures to the different risk factors, we estimate the factor loadings with rolling regressions over 24 months. The statistical significance of the factor loadings and the alpha is estimated based on HAC-adjusted standard errors.[5]

4 Empirical analysis

4.1 Investigating the alpha

For the assessment of the risk-adjusted performance we focus on the alpha from the factor models based on the stepwise regression approach as well as on the Fung and Hsieh (2004) seven-factor model. We estimate the alpha on the level of single hedge funds as well as of hedge fund strategy indices.

Table 3 reports the alphas of the equally-weighted strategy indices based on desmoothed return series. Based on both factor models we find a positive alpha for almost all strategy indices irrespective of the estimation methodology (i.e., constant factor loading OLS and rolling-window OLS), with one exception: the Emerging Market index exhibits a negative alpha of -8bps per month based on the Fung and Hsieh (2004) seven-factor model, when estimated with constant factor OLS. Particularly high alphas are observed for the strategies Dedicated Short Bias, Managed Futures, and Multi-Strategy. Although being positive for all estimation procedures, the alpha of Funds of Funds is among the two lowest in each estimation. The alpha based on the rolling-window estimation is in general higher than the alpha based on constant factor loadings. The last row of Table 3 shows that the average alpha over all strategy indices is positive for both factors models and estimation methodologies but significant only when estimated with rolling-window OLS.

[5] Albeit often used in the literature, we cannot think of an economic justification for the choice of a 24-month window for the estimation of the rolling regression. Therefore, we have also tested other lengths for the estimation window (e.g., 12, 36, and 48 months), which does not alter the conclusion. If we reduce (increase) the length of the window we report a slightly lower (higher) average alpha.

Columns '$R^2(adj)$' and '$FH\ R^2(adj)$' in Table 3 confirm that, consistent with Titman and Tiu (2008), we find higher r-squares based on the stepwise regression factor model as compared to the Fung and Hsieh (2004) model. This presumably stems from the fact that the stepwise regression model is less susceptible with respect to omitted variables. The differences in r-squares are particularly large for the strategies Convertible Arbitrage, Emerging Markets, and Event Driven. This can be explained by the addition of a convertible bond factor, the emerging markets equities factor, and the out-of-the money option factors in the factor model based on stepwise regression. These are factors which are often selected by the stepwise regressions but are not included in the original set of Fung and Hsieh (2004). Furthermore, the stepwise regression model often chooses less than seven factors and thereby conserves degrees of freedom as compared to the Fung and Hsieh (2004) model. This helps to increase the adjusted r-squares of the factor model.

Unlike Table 3, where the alphas are estimated based on the indices for each strategy, Table 4 reports the average alpha of all single funds within a strategy. As we have a highly unbalanced panel, these results are biased to a more recent time period, when the number of funds in our sample is much larger. In addition to the statistics reported in Table 3, Table 4 reports the percentage of funds generating a positive and on the 95% confidence level statistically significant alpha. For the model with constant factor loadings the statistical significance is directly measured by the t-statistic of the alpha. For the rolling-window regressions, alpha is considered significant when its t-value over time exceeds the critical value on the 95% confidence level in a one-sided test. The results in Table 4 show that the average fund again exhibits a positive alpha (with the exception of the average fund of fund when benchmarked against the stepwise factor model). When comparing the results in Tables 3 and 4, we observe that the cross-sectional alpha over all funds is lower than the average alpha over all strategy indices in the time series. Consistently, the alpha in the cross-section is lower for most strategies as compared to the alpha based on the corresponding equally-weighted index. In addition, Table 4 shows that roughly 20% of the funds are able to deliver a significant alpha when benchmarked against the constant loading factor models and 50% when benchmarked against the rolling-window OLS models. Hence, more managers are able to outperform the benchmark when benchmarked against a rolling-window factor model, as compared to a constant loading factor model. Finally, on average, the seven-factor model is outperformed by more funds than the factor model in which the factors are selected based on stepwise regression.

To account for the unsystematic risk, we aditionally investigate the Appraisal ratio, which is defined as the alpha divided by the residual standard deviation from the alpha-regression of the respective fund. Table 5 reports the Appraisal ratio for the equally-weighted strategy indices. Similar to the estimation of the alpha based on the equally-weighted indices in Table 3, we observe high Appraisal ratios for the Multi Strategy index while Funds of Funds again rank amongst the least favorable strategies in all estimations. Furthermore, a high Appraisal ratio is observed for the Equity Market Neutral strategy index. Obviously the adjustment of the alpha for the unsystematic risk does not alter our main results.

So far we have conducted all analyses based on desmoothed single fund return data or based on equally-weighted strategy indices of desmoothed returns. The desmoothing of the reported returns as suggested by Getmansky et al. (2004) leads to a reduction in the average alpha over all strategy indices of four basis points on average (results not reported). This reduction in alpha tends to be higher for strategies investing in less liquid assets (e.g., Funds of Funds and Convertible Arbitrage) as compared to strategies investing in highly liquid assets (e.g., Managed Futures). In fact, when replicating Table 5 based on reported returns, we find the effect of the desmoothing to be more pronounced, particularly for strategies that invest in illiquid assets (results not reported). This makes intuitively sense, as the standard error of the residuals of the regression in the denominator of the Appraisal ratio is strongly affected by the smoothing of the returns (see Getmansky et al., 2004). The desmoothing even alters the ranking of the strategies as measured by the Appraisal ratio. Strategies that invest in less liquid assets turn out to be relatively less attractive than those predominantly investing in highly liquid assets.

For the majority of analyses in this paper we use equally-weighted strategy indices and not value-weighted indices. An advantage of value-weighted indices is that they rather reflect the hedge fund universe and consequently are more likely to reflect an investable strategy. However, they are more sensitive with respect to the quality of the assets under management data. The main caveat of an equally-weighted index is that it implicitly assumes a monthly rebalancing of the portfolio (due to fund flows, however, this also applies to value-weighted indices). Furthermore, an equally-weighted index is less sensitive with respect to certain incidents affecting large funds such as the fall of LTCM (which, however, is not included in our dataset) or the wrong figures reported by Fairfield Greenwich (a large feeder fund of Bernhard L. Madoff Securities). However, we find that the choice of the index does only have a small impact on our results. Overall, the monthly alpha based on the value-weighted indices increases by five to 12 basis points as compared to the equally-weighted indices. This suggests that either some large funds perform very well or some small funds perform relatively poorly.

4.2 Is alpha disappearing?

Fung et al. (2008) argue that the hedge fund industry has experienced several structural breaks. They find the break points to coincide with extreme market events which might have affected managers' risk taking behavior. Based on an index of funds of funds, they identify these break points to be the collapse of Long-Term Capital Management (LTCM) in September 1998 and the peak of the technology bubble in March 2000. The identical structural breaks have also been identified by Naik et al. (2007). Meligkotsidou and Vrontos (2008) investigate structural breaks on the level of hedge fund strategies as well as on overall hedge fund indices over the period January 1994 to November 2005. For the majority of single strategy indices they find the same two break points.

We follow Fung et al. (2008) and apply the factor model of Fung and Hsieh (2004) to the returns of an equally-weighted index of funds of funds and conduct multiple Chow (1960) tests for the above-mentioned and other possible structural breaks. In doing so, we are able to confirm structural breaks in September 1998 and March 2000, both on a 99% confidence level. Furthermore, we identify another structural break at the beginning of a long period of low volatilities in equity markets in early 2004.[6] Finally, we find a fourth break in August 2007 after the liquidity shock in the financial industry.[7] Khandani and Lo (2007) argue that the sharp decrease of the S&P index on August 9, 2007 forced many hedge fund managers to de-leverage their portfolio leading to large losses for highly leveraged hedge funds. However, the null hypothesis of identical coefficients can only be rejected on a confidence level of 94%. Nevertheless, based on the knowledge of the importance of the events in summer 2007 for the hedge fund industry, we decide to run a separate OLS estimation for the time period from August 2007 to September 2008.

Fung et al. (2008) find that the average fund of fund has only delivered positive alpha during the short period from October 1998 to March 2000. We reassess this finding based on a more recent sample of single hedge funds and funds of funds. Table 6 reports the results from a constant factor loading alpha estimation based on equally-weighted desmoothed strategy indices for the five subperiods determined by the four structural breaks. When investigating specific subperiods, alpha varies greatly between the strategies as well as for specific strategies in different subperiods. Consistent with Fung et al. (2008), we find that until 2004 funds of funds only generate a statistically significant positive alpha during the short period from October 1998 to March 2000 based on the Fung and Hsieh (2004) seven-factor model (see Panel B in Table 6). Based on the stepwise model, funds of funds fail to exhibit a statistically significant positive alpha in any of the subperiods. Their estimated alpha is even negative for most subperiods. Furthermore, an investigation of the reported adjusted r-squares suggests that the stepwise regression model is often capable to explain more of the systematic risk exposure than the seven-factor model of Fung and Hsieh (2004). Looking beyond the end of the Fung et al. (2008) sample in December 2004 (Panels D and E), we find a statistically significant positive alpha for funds of funds in the period April 2004 to July 2007 based on the Fung and Hsieh (2004) factor model.[8] Therefore, our results challenge Fung et al.'s (2008)

[6] In February 2004 the Volatitilty Index of the CBOT (VIX) dropped below 15% and remained in the range of 10–15% until June 2007.

[7] August 2007 can be considered as the start of the recent liquidity crisis of 2008. During August 2007 the spread between the 3M USD Libor and the 3M OIS rate increased from 12 to 74 basis points.

[8] The HAC-adjusted t-value of the alpha for funds of funds increases from 1.8 to 2.2, if only the period

finding of a reduction of hedge fund alpha over time.

Figure 1 displays the average alpha of all hedge funds in our sample. The top graph is based on the eleven distinct and strategy-specific factor models estimated with stepwise regressions and the second graph plots the alpha based on the Fung and Hsieh (2004) seven-factor model. The bars in the bottom part of the figure report the monthly attrition rates of the funds in our sample and the line chart displays the number of hedge funds in the sample over time. The first estimated alpha corresponds to the end of 1996 as the rolling regressions require 24 monthly observations.

Figure 1 shows that both factor models lead to qualitatively very similar results. However, the model based on stepwise regression yields a slightly lower alpha (the overall mean alpha based on stepwise regression amounts to 9bps and 23bps based on the Fung and Hsieh (2004) seven-factor model). The average alpha based on both models is almost always positive. In unreported results, we break down Figure 1 by strategies. In general, the results do not exhibit a clear time pattern of the alpha and the differences between the two models are small. The only exception is the strategy Emerging Markets where we find a clear difference in the risk-adjusted performance resulting from the two models. For this strategy index, based on the stepwise regression model, we find a decreasing alpha after 2002. Based on the Fung and Hsieh (2004) model, the alpha experienced several peaks after 2000 and has always been positive.[9]

The attrition rate might be related to hedge fund performance. On the one hand, we could expect a negative relationship between alpha and the attrition rate because a decreasing alpha may lead more hedge funds to stop reporting. On the other hand, there could be a counteracting effect when hedge funds with lower or negative alphas stop reporting to the database (or liquidate the fund). This may lead to a subsequent increase in average alpha. We investigate a potential relationship between alpha and the attrition rate by running regressions of the monthly attrition rate on the average monthly alpha with different leads and lags. We

subsequent to their sample, i.e., January 2005 to July 2007, is considered.

[9]These results are available from the authors upon request.

find a negative and significant relation between the attrition rate and alpha. The highest significance level (p-value of 0.2%) is found for an alpha with a lag of two months. However, for all leads and lags of up to three months we find a negative relationship between the attrition rate and the average alpha, which is significant at the 1% level. This suggests that the attrition rate is higher in times of low hedge fund alphas. However, the adjusted r-squares of these regressions suggest that the attrition rate is only able to explain approximately 5% of the future alphas.

To compare our results with those of Fung et al. (2008), we report the alpha of the equally-weighted index of funds of funds separately in Figure 2. The results based on the seven-factor model (in the bottom part) confirm that the alpha is highest over the two-year period prior to spring 2000. Then, and consistent with Fung et al. (2008), we find the alpha to decrease until the end of their sample period in 2004. However, Figure 2 shows that alpha increases again during the bull market of 2006 and 2007. The results based on the stepwise regression model in the top part of Figure 2 are qualitatively similar. These results clearly challenge the finding of Fung et al. (2008) that fund of funds' alpha is decreasing.[10]

4.3 Fund flows and alpha

In this section, we investigate the relationship between fund flows and alpha. Recent research investigates whether there are capacity constraints in the hedge fund industry. Fung et al. (2008) investigate the relation between fund flows and hedge fund alpha at a single fund level for funds of funds and Naik et al. (2007) on the index level for eight different strategies. The samples of both these papers cover the time period from January 1994 to December 2004. Both papers find empirical evidence that fund flows negatively affect the future alpha. Specifically, Fung et al. (2008) investigate fund flows and alpha on a single fund basis and conclude that funds which generated an alpha in the past and experience above median capital inflows, are more likely to loose their ability to generate a statistically significant alpha in the

[10] Note that unlike when estimating the average alpha over all individual hedge funds, when estimating the alpha based on an index of funds, already the very first observation of each fund (after the first 23 observations of the entire sample period) is included in the alpha estimate. Therefore, when estimating the alpha based on an index, we do not 'loose' the first non-backfilled observations of each fund.

future. Naik et al. (2007) find that fund inflows on a strategy level negatively impact future alpha for four out of their eight strategies (Relative Value, Emerging Markets, Fixed Income, and Directional Traders). With the exception of Directional Traders, these results suggest that strategies investing in less liquid assets are more prone to capacity constraints.

Zhong (2008) also investigates the relationship between fund flows and alpha and finds that the impact of fund flows on performance depends on fund size. His analysis suggests that capital inflows at a fund level have a positive impact on a fund's future performance for smaller funds while for large funds capital inflows impair future performance. Fund flows at a strategy level, however, increase the competition within the strategy and always have a negative impact on the future performance. Given the impact of capital flows and performance, his findings indicate that capacity constraints arise from both limited profitable opportunities within a strategy and the unscalability of managers' abilities.

We study the relationship between fund flows and performance on a single fund level. Therefore, the fund flows for each fund need to be determined. We follow a similar approach as Titman and Tiu (2008) and Fung et al. (2008) and compile the monthly relative net fund flows for each fund for which assets under management are reported. If a fund does not report the assets under management for a particular month, we interpolate the figure linearly over time. When the first or the last entry for assets under management is missing, we write the first or last entry backward and forward. Fund flows into fund i in month t ($F_{i,t}$) are calculated as a function of the current and the lagged assets under management and the monthly returns:

$$F_{i,t} = \frac{AuM_{i,t} - AuM_{i,t-1}(1 + r_{i,t})}{AuM_{i,t-1}} \tag{4}$$

Capital inflows are treated as if they were received at the end of each month. For the calculation of the annual fund flows, the monthly absolute fund flows are aggregated and calculated in relation to the assets under management of each fund (AuM_i) a year earlier.

To explore the existence of capacity constraints at the single fund level, we follow Fung et al. (2008) and investigate the relationship of historical fund flows and a fund's ability to generate alpha in the future. As a first step, we run a regression of each fund's return against the Fung and Hsieh (2004) seven-factor model over the 24-month window from October 1994 to September 1996. This period is used as the first classification period to identify funds with a statistically significant positive alpha at the 5% level. These funds are classified as 'have-alpha' funds. Among the have-alpha funds, we form two sub-portfolios of those funds that have experienced above median and below median relative net asset inflows over the second year of the two-year classification period. We then test the statistical significance of the alpha of these funds out-of-sample in the two years following the classification period. From this out-of-sample test we calculate the proportion of funds in each portfolio that remain have-alpha funds and the proportion of funds migrating to beta-only funds or to funds which stop reporting to the database. This test is yearly rolled forward in time; the last classification period ends in September 2006 and is applied out-of-sample to the performance of the funds during the period October 2006 to September 2008.

In Table 7, we compare the two-year transition probabilities of the have-alpha funds with above and below median fund flows. Over the entire sample period (the average over the classification periods 1996–2006) we observe that the migration probability of have-alpha funds to beta-only funds or funds that stop reporting is smaller for funds which experienced above-median asset inflows in the second year of the classification period. Therefore, our results contradict the finding of Fung et al. (2008) that have-alpha funds with above median net asset inflows are more likely to migrate to beta-only funds or funds that stop reporting to the database. We therefore split our sample into two sub-periods in September 2001 (classification period) to obtain the same time period as Fung et al. (2008) and the subsequent period from October 2001 to September 2006. In fact, our results confirm those of Fung et al. (2008) in the first sub-period. We find the migration probability of have-alpha funds to be greater for funds which experienced above-median asset inflows in the second year of the classification period. The only exception are the portfolios formed during the classification period October 1996 to September 1998 and tested for future alpha in the period October 1998 to September 2000. The funds of funds in the sample of Fung et al. (2008) in the classification period

January 1996 to December 1998 exhibit the same pattern. However, our results suggest that after September 2001 have-alpha funds with above median net capital inflows are more likely to remain have-alpha funds in the following two-year period than funds with below median capital inflows. A contingency table test that the above and below-median flow transition probabilities are identical, suggests that the findings of a positive relationship between fund flows and future alpha for the second part of the sample is statistically significant.[11] This finding challenges the conclusion of Fung et al. (2008) that capital flows on a single fund level adversely affect their risk-adjusted performance. Hence, we find no support for the hypothesis of capacity constraints at the level of single hedge funds.

5 Conclusion

This paper investigates the development of hedge fund alpha over the time period from 1994 to 2008 based on the Lipper/TASS database. We estimate alpha by benchmarking hedge fund returns against two alternative return-based factor models. Specifically, we establish a factor model in which we select the risk factors based on a stepwise regression approach, and compare the results to the widely used factor model proposed by Fung and Hsieh (2004). We account for the dynamics in the factor exposures by using a rolling-window regression approach.

Most importantly, we find no systematically decreasing alpha in the hedge fund industry over time. This finding contradicts Fung et al. (2008) and Zhong (2008) who both report decreasing hedge fund alphas over the time period 1994 to 2004. In addition, we find no evidence pointing to capacity constraints in the hedge fund industry. In fact, we find that there is a positive relationship between fund flows and future alpha. These results are qualitatively insensitive with respect to how alpha is measured.

[11] In unreported results, we have also conducted the same analysis with the factor model based on stepwise regression and obtained qualitatively similar results. The results are available from the authors upon request.

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Table 1: Theta estimates for all strategies
This table shows the results from the estimation of θ_0, θ_1, and θ_2 based on the methodology of Getmansky et al. (2004) applied to our sample of single hedge funds for each strategy. The last two columns report the number of funds in our sample for each strategy including (N) and excluding ($N_{(AuMadj.)}$) funds with less than USD 5m assets under management.

	θ_0	θ_1	θ_2	N	$N_{(AuMadj.)}$
Convertible Arbitrage	0.7191	0.2128	0.0680	138	135
Dedicated Short Bias	1.0382	0.0371	-0.0753	21	20
Emerging Markets	0.8651	0.1343	0.0007	237	230
Equity Market Neutral	1.0195	-0.0208	0.0013	216	200
Event Driven	0.7832	0.1504	0.0664	355	347
Fixed Income Arbitrage	0.8639	0.1051	0.0310	173	169
Fund of Funds	0.7649	0.1882	0.0469	716	661
Global Macro	1.0686	-0.0012	-0.0674	180	167
Long/Short Equity	0.9512	0.0611	-0.0123	1,209	1,140
Managed Futures	1.0244	-0.0127	-0.0117	301	244
Multi Strategy	0.8461	0.0821	0.0718	192	178

Table 2: Factor selection for each hedge fund strategy
This table shows the factors selected from the stepwise regression applied to the equally-weighted indices of our sample for each strategy. For each strategy, we use a separate set of risk factors to be able to better reflect peculiarities of the strategy. These risk factors are selected from 23 potential risk factors. The full choice of factors is provided in Appendix A.

Convertible Arbitrage	**Dedicated Short Bias**	**Emerging Markets**
CS High Yield Index II	Russel 3000	MSCI EM
Delta Baa Spread*	SMB*	MoM*
Delta 3M TED Spread*		Dollar Index spot
Russel 3000		
SPX Call 107.5%		
ML Convertible Bond Index (IG)		
Equity Market Neutral	**Event Driven**	**Multi-Strategy**
SPX ATM Call	CS High Yield Index II	MSCI EM
CS High Yield Index II	MSCI EM	Delta 3M TED Spread*
MOM*	SPX Put 92.5%	MSCI World Ex US
	SMB	SMB*
	SPX Call 107.5%	CS High Yield Index II
	Delta 3M TED Spread*	S&P GS Commodity Index
Fixed Income Arbitrage	**Global Macro**	**Long/Short Equity**
Delta 3M TED Spread*	Delta 3M TED Spread*	MSCI EM
CS High Yield Index II	PTFSFX**	VIX
PTFSBD**	Delta Baa Spread	Russel 3000
	MoM*	MoM*
	CS High Yield Index II	ML Convertible Bond Index (IG)
	SPX ATM Call	SMB*
	S&P GS Commodity Index	Delta 3M TED Spread*
Managed Futures	**Funds of Funds**	
PTFSFX**	MSCI EM	
PTFSBD**	Delta 3M TED Spread*	
PTFSFX**	SPX ATM Call	
S&P GS Commodity Index	SPX ATM Put	
Citi World Govt Bond Index	PTFSCOM**	
Dollar Index spot	MOM	
	SMB	

** All indices are excess returns over the 1m T-Bill except those indicated with an asterisk (*)*
*** Primitive Trend Following Strategies on: BD: Bonds, STK: Stocks, FX: Currencies, COM: Commodities*

Table 3: Alphas of equally-weigthed hedge fund strategy indices
The table reports alphas estimated with two alternative factor models and two different estimation methodologies for eleven different hedge fund strategies. The two factor models investigated include a factor model that selects the risk factors based on stepwise regression and the Fung and Hsieh (2004) seven-factor model (FH). The factor models are estimated based on a constant-loading OLS approach and an OLS estimation over rolling 24-months windows. The table is based on equally-weighted indices of all USD denominated funds with at least 24 non-backfilled observations for each strategy. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004). All alphas are expressed in monthly percentage returns. N indicates the number of funds in each strategy. The asterisks *, **, and *** indicate statistical significance on the 90%, 95%, and 99% conficence level (two-sided) based on HAC-adjusted error terms.

	Factor Model based on stepwise regression			Fung and Hsieh (2004) 7-factor model			
Strategy	α_{OLS}	R^2 (adj)	$\alpha_{OLS24mroll}$	$\alpha_{OLS,FH}$	FH R^2 (adj)	$\alpha_{OLS24mroll}, FH$	# Funds (N)
Convertible Arbitrage	0.28**	0.66	0.38***	0.17	0.33	0.39***	135
Dedicated Short Bias	0.45**	0.61	0.52***	0.48**	0.60	0.36***	20
Emerging Markets	0.16	0.81	0.33***	-0.08	0.44	0.04	230
Equity Market Neutral	0.30***	0.30	0.29***	0.33***	0.06	0.29***	200
Event Driven	0.15*	0.69	0.20***	0.18*	0.51	0.30***	347
Fixed Income Arbitrage	0.10	0.30	0.16***	0.10	0.10	0.19***	169
Fund of Funds	0.03	0.75	0.08***	0.00	0.46	0.04	661
Global Macro	0.15	0.37	0.16***	0.14	0.24	0.07*	167
Long/Short Equity Hedge	0.22**	0.88	0.23***	0.30**	0.76	0.42***	1,140
Managed Futures	0.50**	0.34	0.26***	0.69***	0.29	0.44***	244
Multi-Strategy	0.34***	0.48	0.38***	0.28**	0.29	0.39***	178
Average	0.24	0.56	0.28***	0.23	0.37	0.27***	3,491

Table 4: Average alphas of single funds within each strategy

The table reports alphas estimated with two alternative factor models and two different estimation methodologies for eleven different hedge fund strategies. The two factor models investigated include a factor model that selects the risk factors based on stepwise regression and the Fung and Hsieh (2004) seven-factor model (FH). The factor models are estimated based on a constant-loading OLS approach and an OLS estimation over rolling 24-months windows. The table is based on all USD denominated funds with at least 24 non-backfilled observations. N indicates the number of funds in each sample and Nt the number of fund-month observations underlying the alpha estimate. For rolling OLS the first 23 observations of each fund are lost for estimating the first alpha. The column 'sign. α' reports the proportion of funds in the respective strategies that exhibit an alpha that is greater than zero on a confidence level of 95% (based on HAC-adjusted standard errors) based on the constant factor loading OLS regression and the column 'sign. α_{roll}' reports the proportion of funds that have a siginficantly positive average alpha over time when estimating the alpha over 24 months with rolling regression. The bottom row includes the average alpha over all funds in the cross-section. All alphas are expressed in monthly percentage returns. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004). The asterisks *, **, and *** indicate statistical significance on the 90%, 95%, and 99% conficence level (one-sided) based on HAC-adjusted error terms.

	Factor Model based on stepwise regression					Fung and Hsieh (2004) seven-factor model					# Funds		Nt
Strategy	α_{OLS}	R^2 (adj)	α_{roll}	sign. α	sign. α_{roll}	α_{OLS}	R^2 (adj)	α_{roll}	sign. α	sign. α_{roll}	(N)	Nt	(roll)
Convertible Arbitrage	0.14**	0.37	0.13	27%	49%	0.06	0.14	0.21***	16%	60%	138	8,666	5,492
Dedicated Short Bias	0.21	0.62	0.23	14%	38%	0.16	0.62	0.13	24%	33%	21	1,289	806
Emerging Markets	0.22***	0.42	0.34***	15%	49%	0.18**	0.24	0.38***	16%	59%	237	15,089	9,638
Equity Market Neutral	0.10***	0.15	0.10**	25%	54%	0.12***	0.11	0.12***	25%	55%	216	11,875	6,907
Event Driven	0.20***	0.35	0.39***	25%	52%	0.19***	0.25	0.35***	33%	67%	355	21,763	13598
Fixed Income Arbitrage	0.06	0.15	0.13***	31%	60%	0.06	0.11	0.16***	32%	59%	173	9,939	5,960
Fund of Funds	-0.05**	0.52	-0.02	16%	43%	-0.09***	0.32	0.08***	10%	57%	716	41,772	25,304
Global Macro	0.05	0.17	0.03	23%	54%	0.02	0.15	0.02	21%	47%	180	9,678	5,538
Long/Short Equity Hedge	0.00	0.42	0.02	17%	43%	0.15***	0.31	0.27***	18%	57%	1,209	69,092	41,285
Managed Futures	0.18	0.21	0.12	13%	34%	0.38**	0.16	0.38*	16%	46%	301	15,527	8,604
Multi-Strategy	0.13**	0.31	0.08	27%	45%	0.19***	0.19	0.30***	32%	64%	192	12,073	7,657
Average (cross-section)	0.06***	0.37	0.09***	19%	46%	0.12	0.25	0.23	20%	57%	3,738	216,763	130,789

Table 5: Appraisal ratios based on indices of equally-weighted returns
The table reports Appraisal ratios estimated with two alternative factor models and two different estimation methodologies. The two factor models investigated include a factor model that selects the risk factors based on stepwise regression and the Fung and Hsieh (2004) seven-factor model (FH). The factor models are estimated based on a constant-loading OLS approach (OLS) and an OLS estimation over rolling 24-months windows (Roll). The table is based on an equally-weighted index for each strategy. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004).

	Stepwise regression		FH 2004 7-factor	
Strategy	Appraisal OLS	Appraisal Roll	Appraisal OLS	Appraisal Roll
Convertible Arbitrage	0.24	0.44	0.10	0.40
Dedicated Short Bias	0.14	0.19	0.15	0.05
Emerging Markets	0.07	0.24	-0.02	0.16
Equity Market Neutral	0.48	0.52	0.46	0.50
Event Driven	0.14	0.41	0.14	0.47
Fixed Income Arbitrage	0.09	0.38	0.09	0.51
Fund of Funds	0.03	0.12	0.00	0.04
Global Macro	0.11	0.16	0.09	0.05
Long/Short Equity Hedge	0.23	0.28	0.22	0.44
Managed Futures	0.18	0.10	0.24	0.22
Multi-Strategy	0.24	0.55	0.17	0.51
Average (time weighted)		0.31		0.31

Table 6: Alphas of equally-weighted indices in different subperiods
The table reports the alphas of the equally-weighted strategy indices estimated with two alternative factor models. The two factor models investigated include a factor model that selects the risk factors based on stepwise regression and the Fung and Hsieh (2004) seven-factor model (FH). The factor models are estimated with constant-loading OLS. The identification of subperiods is based on structural breaks which are obtained from multiple Chow (1960) tests. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004). All alphas are expressed in monthly percentage returns. The asterisks *, **, and *** indicate a statistical significance on the 90%, 95%, and 99% conficence level (two-sided) based on HAC-adjusted error terms.

Strategy	α_{OLS}	adj R^2	$\alpha_{OLS,FH}$	adj R^2 FH
Panel A — Subperiod January 1994 to September 1998				
Convertible Arbitrage	0.30**	0.68	0.38**	0.55
Dedicated Short Bias	1.07	0.57	1.24**	0.52
Emerging Markets	0.26	0.80	-1.92***	0.52
Equity Market Neutral	0.56***	0.08	0.63***	0.08
Event Driven	0.19	0.65	-0.07	0.45
Fixed Income Arbitrage	0.08	0.28	0.19	0.21
Fund of Funds	0.04	0.66	-0.31**	0.62
Global Macro	0.38	0.40	0.45*	0.52
Long/Short Equity Hedge	0.48**	0.87	0.46***	0.80
Managed Futures	0.46	0.55	0.65	0.50
Multi-Strategy	0.61**	0.38	0.16	0.14
Panel B — Subperiod October 1998 to March 2000				
Convertible Arbitrage	1.70***	0.63	1.82***	0.22
Dedicated Short Bias	0.49	0.45	-0.90	0.40
Emerging Markets	-0.32	0.83	0.88	0.24
Equity Market Neutral	0.32*	0.29	0.52**	-0.01
Event Driven	0.88**	0.74	1.23***	0.54
Fixed Income Arbitrage	0.16	0.16	0.92***	0.52
Fund of Funds	0.03	0.76	1.17***	0.65
Global Macro	-0.61**	0.40	-0.47***	0.72
Long/Short Equity Hedge	0.72***	0.97	2.18***	0.88
Managed Futures	-1.19***	0.60	-1.23**	-0.01
Multi-Strategy	0.86***	0.47	1.24***	0.82
Panel C — Subperiod April 2000 to March 2004				
Convertible Arbitrage	0.41	0.58	0.11	0.18
Dedicated Short Bias	-0.18	0.83	-0.3	0.82
Emerging Markets	0.29	0.85	0.27	0.72
Equity Market Neutral	-0.05	0.14	-0.13	0.23
Event Driven	0.09	0.77	0.13	0.62
Fixed Income Arbitrage	0.17*	0.10	0.16*	0.15
Fund of Funds	-0.11	0.69	-0.24***	0.67
Global Macro	0.07	0.49	-0.07	0.55
Long/Short Equity Hedge	-0.14	0.94	-0.19*	0.89
Managed Futures	0.55	0.39	0.92**	0.32
Multi-Strategy	0.23	0.65	0.23**	0.69

Table 6 — continued				
Strategy	α_{OLS}	adj R^2	$\alpha_{OLS,FH}$	adj R^2 FH
Panel D — Subperiod April 2004 to July 2007				
Convertible Arbitrage	-0.32**	0.61	0.00	0.29
Dedicated Short Bias	-0.15	0.93	-0.27	0.91
Emerging Markets	0.11	0.90	1.37***	0.35
Equity Market Neutral	0.07	0.53	0.13	0.27
Event Driven	0.60**	0.74	0.44***	0.72
Fixed Income Arbitrage	0.10	0.47	0.14*	0.30
Fund of Funds	-0.16	0.84	0.31*	0.62
Global Macro	0.10	0.65	0.25	0.44
Long/Short Equity Hedge	-0.03	0.91	0.39**	0.73
Managed Futures	0.22	0.37	0.49*	0.53
Multi-Strategy	-0.13*	0.88	0.41**	0.56

Panel E — Subperiod August 2007 to September 2008				
Convertible Arbitrage	-1.80	0.94	-0.50	0.29
Dedicated Short Bias	0.36	0.92	0.46***	0.96
Emerging Markets	-0.88**	0.89	-0.34	0.43
Equity Market Neutral	-0.45***	0.73	0.07	-0.19
Event Driven	-1.88***	0.94	-0.66*	0.45
Fixed Income Arbitrage	-0.42	0.79	-0.20	0.33
Fund of Funds	-0.25	0.90	-0.49	0.27
Global Macro	-0.07	0.92	0.04	0.11
Long/Short Equity Hedge	-0.46***	0.95	-0.36	0.60
Managed Futures	0.38	0.83	0.95*	-0.14
Multi-Strategy	0.01	0.73	-0.32	0.06

Table 7: Two-year transition probabilities for have-alpha funds
Hedge funds are classified as 'have-alpha' funds if their alpha based on the seven-factor model is positive and significant on the 5% significance level over a two-year classification period (two-sided based on HAC-adjusted standard errors). Funds without a significantly positive alpha are labeled 'beta only' funds. Column 'Proportion have-alpha' reports the proportion of funds that are classified as have-alpha funds. Among the have-alpha funds, we form two sub-portfolios based on whether the funds have experienced above median or below median relative net asset inflows over the second year of the classification period. The last three columns show the two-year transition probabilities of the funds. The column 'have-alpha' reports the proportion of funds that remain have-alpha funds in the next non-overlapping two-year classification period. The following columns report the number of funds that migrate to beta-only funds or funds that stop reporting to TASS. The three bottom rows report p-values from the Chi-square statistics of contingency table tests that the above and below-median flow transition probabilities are identical.

24m Classification Period ends	# of funds	Proportion have-alpha	From / To	have alpha	beta only	stop reporting
Sep-96	9	22%	above median	0%	100%	0%
			below median	0%	100%	0%
Sep-97	145	27%	above median	15%	70%	15%
			below median	32%	42%	26%
Sep-98	304	16%	above median	72%	24%	4%
			below median	32%	36%	32%
Sep-99	413	21%	above median	25%	57%	18%
			below median	35%	49%	16%
Sep-00	540	38%	above median	24%	66%	11%
			below median	28%	57%	15%
Sep-01	597	24%	above median	48%	40%	12%
			below median	60%	33%	7%
Sep-02	652	21%	above median	46%	41%	13%
			below median	44%	38%	18%
Sep-03	1,027	32%	above median	25%	68%	7%
			below median	21%	65%	14%
Sep-04	1,334	30%	above median	36%	49%	15%
			below median	30%	46%	23%
Sep-05	1,504	17%	above median	26%	55%	19%
			below median	18%	49%	33%
Sep-06	1,625	25%	above median	11%	49%	40%
			below median	10%	51%	40%
Average (96–01)	2,008	26%	above median	38%	50%	12%
			below median	40%	44%	16%
Average (01–06)	6,142	25%	above median	26%	53%	21%
			below median	22%	50%	28%
Average (96–06)	8,150	25%	above median	29%	52%	19%
			below median	26%	49%	25%
Contingency table test period 96–01: Chi-square statistic (p-value)					0.42	(0.52)
Contingency table test period 01–06: Chi-square statistic (p-value)					2.80	(0.09)
Contingency table test period 96–06: Chi-square statistic (p-value)					0.95	(0.33)

Figure 1: Alpha over all hedge fund strategies and over time
This figure shows the average alpha of all hedge funds in our sample based on the stepwise regression factor model (top part) and based on the Fung and Hsieh (2004) seven-factor model (bottom part). The bottom part of the figure additionally displays the monthly attrition rate of the funds in our sample and the number of funds included in the estimation of the average alpha in each sample month. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004) and we require 24 non-backfilled observations for a fund to be included in this figure.

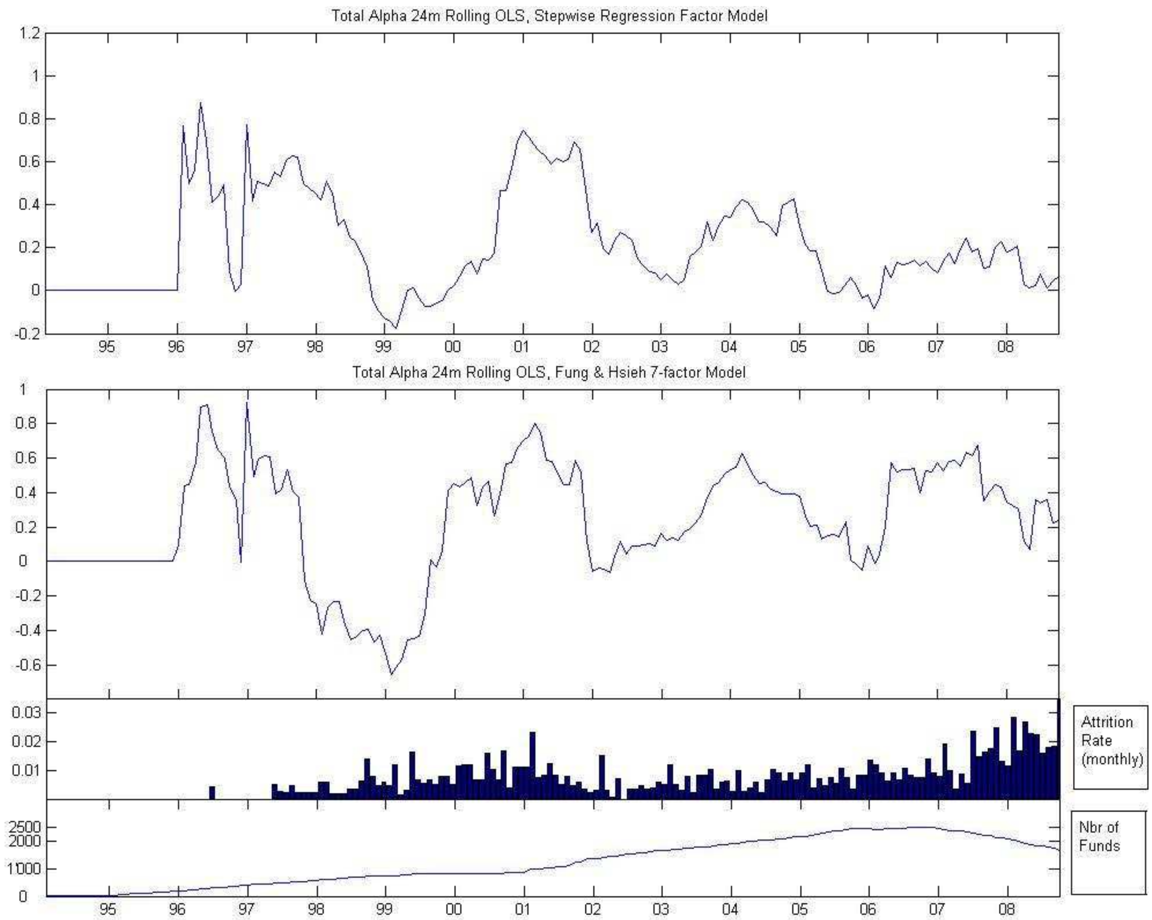
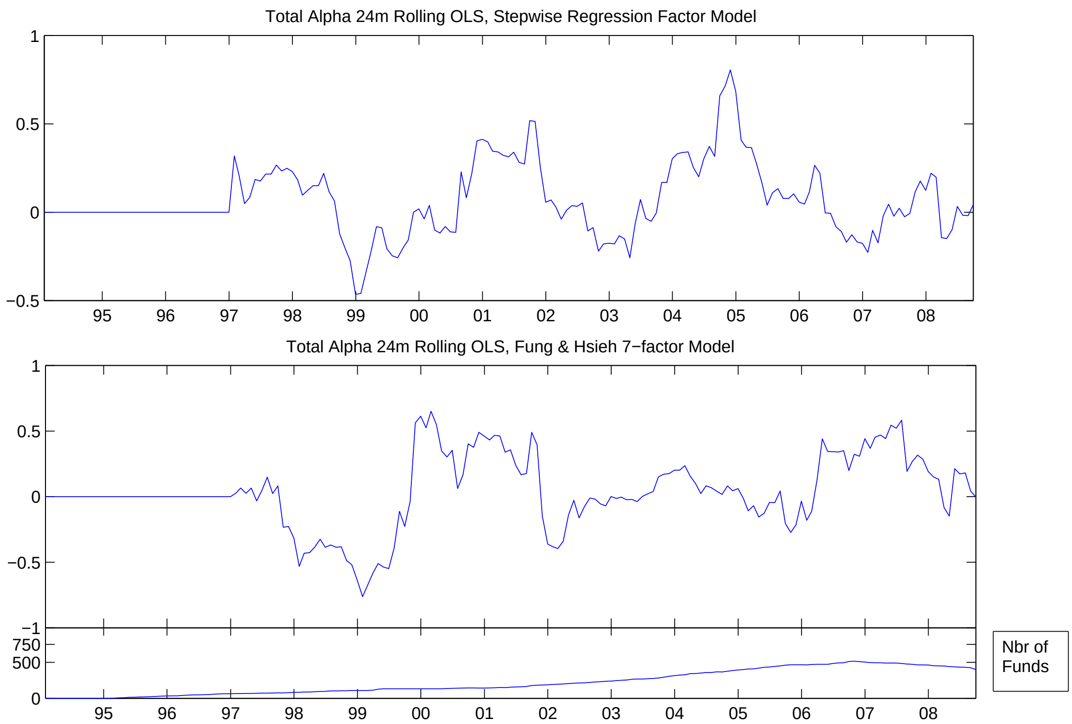


Figure 2: Alpha of funds of hedge funds over time
This figure shows the alpha generated of the equally-weighted strategy index of funds of funds based on the stepwise regression factor model (top part) and based on the Fung and Hsieh (2004) seven-factor model (bottom part). The bottom part of the figure additoinallly displays the number of funds included in the estimation of the average alpha in each sample month. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004) and we require 24 non-backfilled observations for a fund to be included in this figure.



Appendix A: Factors considered for the factor model

- **Equity indices**: excess returns of the following indices: MSCI World EX USA TR USD, MSCI Emerging Markets TR (USD), MSCI Emerging Markets Latam TR (USD), MSCI Emerging Markets ASIA TR (USD), Russel 3000 TR Index

- **Bond indices / Credit Risk / Interest rates**: excess returns, yields, and first differences of the following indices: Citi World Government Bond Index excess return, CS High Yield Index II excess return, monthly first difference of the Moody's Baa Corporate Bond Index 30yr 100m minus the 30yr generic US government bond yield, 3m TED Spread

- **Currency index** excess return of the US Dollar Index return

- **Options/ Volatility/ Dynamic Trading Strategies**: excess returns of the following indices/portfolios: S&P 500 Volatility Index, SMB (Fama and French (1993)), HML (Fama and French (1993)), MOM (Carhart (1997))[12], Black Scholes S&P 500 ATM/OTM call and put options based based on historical implied volatilities and historical realized dividend yields and interest rates of the following moneyness: ATM Call, 107.5% Call, 92.5% Put, ATM Put, Lookback straddles on equities, commodities, currencies, and bonds [13].

- **Commodities**: excess returns of the S&P Goldman Sachs Commodity Index (SP GCSI) total return

- **Real estate**: excess returns of the S&P/Citigroup World REIT Index TR

- **Convertible Bonds**: excess returns for the Merrill Lynch Convertible Bond Index (investment grade)

[12]For the US market, these factors are available from the homepage of Kenneth French.

[13]The returns of these primitive trend following strategies (PTFSBD: Return of PTFS Bond lookback straddle, PTFSFX: Return of PTFS Currency Lookback Straddle, PTFSCOM: Return of PTFS Commodity Lookback Straddle, PTFSIR: Return of PTFS Short Term Interest Rate Lookback Straddle, PTFSSTK: Return of PTFS Stock Index Lookback Straddle) can be downloaded from the homepage of David Hsieh at: http://faculty.fuqua.duke.edu/∼dah7/DataLibrary/TF-Fac.xls.