Investigating Hedge Fund Performance

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Executive Summary

Driven by tremendous historical growth and the recent credit crisis, the hedge fund industry has come to an interesting turning point. This thesis presents three studies on risk-adjusted hedge fund performance to shed some more light on this issue.

A probable consequence of this changed environment is that hedge fund alpha has diminished. The results of the first topic in this thesis indicate that hedge fund alpha has been positive on average, even after accounting for fees and potential biases in reported returns. In addition, and unlike previous research, neither do we find a systematically decreasing hedge fund alpha over time, nor empirical evidence pointing to capacity constraints in the industry.

The second empirical study concludes that the knowledge about historical alpha and other fund characteristics enables investors to form hedge fund portfolios that outperform their peers. Outperformance turns out to be both statistically and economically highly significant. Specifically, we investigate the performance persistence of two-way sorted portfolios, for which the sorting is based on past performance and several additional fund characteristics. Besides a strong alpha persistence, we find only one fund characteristic, a 'Strategy Distinctiveness Index' (SDI), to have the ability to systematically improve alpha performance persistence. The SDI attempts to measure manager skills and the uniqueness of the hedge funds' trading strategies.

Finally, we compare three alternative factor models: The widely used Fung and Hsieh (2004) seven-factor model, a recently proposed extension to an eight-factor model, and a model that selects the relevant risk factors for each strategy based on a stepwise regression approach. The alphas resulting from the three alternative factor models are qualitatively similar over a fairly long period of time. However, during crisis periods, we find substantial differences in alphas (and r-squares) resulting from the Fung and Hsieh (2004) seven-factor model compared to the other two models. Given its much simpler implementation, the eight-factor model seems to be a suitable successor for the widely used seven-factor model.

Zusammenfassung

Nach einer langen Periode grosser Wachstumsraten ist die Hedgefond-Industrie im Kontext der kürzlichen Kreditkrise an einen interessanten Wendepunkt geraten. Diese Dissertation umfasst drei Aufsätze, die sich mit der risiko-adjustierten Performance von Hedgefonds befassen.

Eine mögliche Konsequenz des veränderten Umfeldes ist eine Reduktion der risikoadjustierten Performance (Alpha) von Hedgefonds. Entgegen dieser Hypothese zeigen die Resultate des ersten Aufsatzes ein positives historisches Hedgefondalpha auf. Im Gegensatz zu vorhergehender Forschung finden wir kein systematisch sinkendes Alpha über die Zeit sowie keine empirische Bestätigung für Kapazitätsbeschränkungen.

Der zweite Aufsatz befasst sich mit der Performancepersistenz von Hedgefonds: Er zeigt auf, dass Investoren im Wissen um historische Alphas und weitere Fondscharakteristika Portfolios mit einer systematischen Überrendite gegenüber anderen Portfolios bilden können. Im Besonderen untersuchen wir die Performancepersistenz von Portfolios, welche nach historischem Alpha und verschiedenen anderen Charakteristika sortiert werden. Wir finden dabei eine starke Alphapersistenz. Das einzige zusätzliche Charakteristikum, das die Alphapersistenz systematisch zu erhöhen vermag, ist ein so genannter "Strategy Distinctiveness Index" (SDI). Dieser SDI versucht die Einzigartigkeit der Handelsstrategie von Hedgefondsmanagern zu messen.

Schliesslich vergleichen wir drei verschiedene Faktormodelle zur Performancemessung von Hedgefonds. Wir vergleichen das weit verbreitete sieben-Faktormodell von Fung und Hsieh (2004), eine kürzliche vorgeschlagene Erweiterung desselben zu einem acht-Faktormodell und ein Modell, in welchem die Risikofaktoren für jede Strategie mit einem systematischen statistischen Verfahren, der so genannten Stepwise Regression, selektiert werden. Wir finden dass die Alphaschätzungen aller drei Modelle über eine relativ lange Zeit ähnlich sind. Nicht jedoch während Krisenperioden, in welchen wir substantielle Unterschiede zwischen dem Fung und Hsieh (2004) Modell und den anderen beiden Modellen feststellen. Angesichts der einfacheren Implementierung des acht-Faktormodelles verglichen mit dem Stepwise Regression Modell, empfehlen wir das acht-Faktormodell als passenden Nachfolger für das verbreitete Modell von Fung und Hsieh (2004).

Chapter 1

Introduction

With a focus on alpha, the thesis at hand investigates risk-adjusted hedge fund performance based on different risk factor models. Within the broad field of research on hedge fund performance, the thesis addresses three topics. First, it investigates the historical development of hedge fund alpha. Previous research suggests that it has declined over time due to increased competition and an unscalability of hedge fund managers' skills. Second, the question of performance persistence of hedge fund portfolios is addressed and it is shown that portfolios formed based on certain hedge fund characteristics can systematically outperform other hedge fund portfolios. Third, the thesis compares the sensitivity of alpha estimates with respect to the choice of the factor model. We suggest that an extension of the widely used seven-factor model, introduced by Fung and Hsieh (2004), is a good choice for a broadly used factor model. Including an emerging markets risk factor, the resulting eight-factor model is a competitive successor for the Fung and Hsieh (2004) seven-factor model.

Motivation

The amount of capital invested in the hedge fund industry has considerably increased since 1994. According to the TASS Asset Flow Report, the assets under management by hedge funds (excluding funds of funds) are estimated to have increased from roughly USD 50bn in January 1994 to USD 1,090bn in June 2009, with a peak of 1,546bn in June 2007. This corresponds to an average annual growth rate of 22%. The massive change in size of this asset class and the improved availability of data affect both relevance and reliability of research on hedge fund performance. Furthermore, due to its increased size and the recent credit crisis, the hedge fund industry has come to an interesting turning point. For these reasons, this doctoral thesis is dedicated to this topic. The three studies on hedge fund performance included herein, add to the literature by providing additional insights on hedge fund performance.

1.1 Results and Contribution to the existing Literature

This section provides an overview of the main results of this thesis and its contribution to the existing literature. Section 1.1.1 summarizes the findings of the first empirical study of this thesis presented in Chapter 2 on the development of the alpha over time. Section 1.1.2 presents the major findings on hedge fund performance persistence studied in Chapter 3. The main findings of Chapter 4 on the comparison of three different factor models are outlined in Section 1.1.3.

1.1.1 Has Hedge Fund Alpha disappeared?

Chapter 2 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 (e.g., Fung et al., 2008; Zhong, 2008). Moreover, based on our sample, we cannot confirm prior evidence pointing to capacity constraints in the hedge fund industry (e.g., Naik et al., 2007; Fung et al., 2008).

1.1.2 Hedge Fund Characteristics and Performance Persistence

In Chapter 3 we investigate the performance persistence of hedge funds over time horizons of 6 to 36 months, based on a merged sample from the Lipper/TASS and CISDM databases for the time period from 1994 to 2008. Unlike previous research, we use a panel probit regression approach to identify fund characteristics that are significantly related to performance persistence. We then investigate the performance of two-way sorted portfolios where sorting is based on past performance and one of the additional fund characteristics identified as persistence-enhancing in the probit analysis. We find statistically and economically significant performance persistence for time horizons of up to 36 months. Although we identify several fund characteristics that are strongly correlated with the probability of observing performance persistence, we only find one fund characteristic to have the ability to systematically improve performance persistence up to a time horizon of 24 months. The respective characteristic is a Strategy Distinctiveness Index that attempts to measure manager skills and the uniqueness of the hedge fund's trading strategies. The economic magnitude of this improvement amounts to a sizeable increase in alpha by approximately 4.0% and 2.3% p.a. for annual and biennial rebalancing, respectively.

1.1.3 Benchmarking Hedge Funds: The Choice of the Factor Model

There is yet no consensus regarding a generally accepted factor model to assess risk-adjusted hedge fund performance. Therefore, we compare three alternative factor models in Chapter 4: The widely used Fung and Hsieh (2004) seven-factor model, a recently proposed extension to an eight-factor model, and a model that selects the relevant risk factors based on a forward stepwise regression approach. In our sample from 1994 to 2009, the differences in alphas resulting from the three alternative factor models are small over fairly long time periods. However, during crisis periods, such as the recent credit crisis, we find a substantial difference in the alphas resulting from the Fung and Hsieh (2004) seven-factor model compared to the other two models. The emerging markets factor, which is included in the eight-factor model and which is also in the stepwise-based model for 7 out of 11 hedge fund strategies, seems to capture a large part of hedge fund return volatility during crisis periods. Both the stepwise and the eight-factor model generate qualitatively similar results, even on the strategy level. Unlike the stepwise-based factor model, the eight-factor uses the same set of risk factors for all hedge fund strategies. Hence, given its computationally much simpler implementation, the eight-factor model seems to be a good choice for a broadly used factor model and a suitable successor for the widely used seven-factor model.

1.2 Structure of the Thesis

The remainder of this thesis is organized as follows: Chapter 2 investigates the alpha generation of the hedge fund industry in the cross section and in the time series. Unlike previous research, it finds no evidence for decreasing hedge fund alpha over time and it challenges the hypothesis of capacity constraints for alpha generation in the hedge fund industry. Chapter 3 investigates hedge fund characteristics and performance persistence and proposes an approach to form hedge fund portfolios that outperform their peers, both in terms of economically relevant size and statistical significance. Chapter 4 compares three different factor models to estimate hedge fund alpha and finds that the inclusion of an emerging markets index as a risk factor significantly increases the explanatory power of the widely used seven-factor model suggested by Fung and Hsieh (2004), especially in crisis periods. Given its computationally straightforward implementation, it is suggested as a suitable successor for the widely used Fung and Hsieh (2004) seven-factor model. Chapter 5 summarizes the major findings of this thesis and concludes.

Chapter 2

Has Hedge Fund Alpha disappeared?

2.1 Introduction

This chapter 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., 2010; 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

[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.

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 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.

This chapter contributes to the existing literature by investigating hedge fund alpha based on a recent and comprehensive data set compiled from the Lipper/TASS database 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. The stepwise regression procedure attempts to determine the statistically optimal combination of risk factors to be included in the factor model. We then compare the results from this stepwise regression approach to those obtained based on the widely used factor model proposed by Fung and Hsieh (2004). In the factor model based on stepwise regression, we account for the possible nonlinearity 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 and for the majority of strategies. In general, we find qualitatively similar results based on both alternative factor models throughout the chapter. However, for certain hedge fund strategies 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, an emerging markets equity factor, and the out-of-the money option factors in the factor models based on stepwise regression, respectively. These factors are not included in the original set of Fung and Hsieh (2004). The effect on alpha resulting from the two alternative models, however, is often very small even when the explanatory power largely differs.

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 chapter proceeds as follows. Section 2.2 describes the underlying data set. Section 2.3 describes the methodology applied for the analysis at hand. Section 2.4 summarizes the results of the analysis and Section 2.5 concludes.

2.2 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.[2]

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. (2004a).[3]

Getmansky et al. (2004a) 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

[2]Due to multiple share classes and onshore and offshore funds, our sample might contain some duplicated funds. This might affect our results on hedge fund alpha as better funds are more likely to have multiple entry points in our sample. However, different series of one particular hedge fund are often denominated in different currencies and as we only consider funds reporting in USD many of those duplicated funds are dropped from our sample. In addition, such a double counting of funds only affects the equally-weighted index as the value-weighted index weights each single share class of a hedge fund based on its particular assets under management. As the results from the equally- and value-weighted analyses are qualitatively identical, we believe that a potential bias arising from double counting to be small.

[3]Jagannathan et al. (2010) find that this procedure of desmoothing the returns leads to a reduction of hedge fund alpha.

relationship with actual returns:

$$R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \cdots + \theta_k R_{t-k} \tag{2.1}$$

$$\text{with} \quad \theta_j \in [0,1], \qquad j = 0, \ldots, k \tag{2.2}$$

$$\text{and} \quad 1 = \theta_0 + \theta_1 + \cdots + \theta_k \tag{2.3}$$

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.[4] We use these thetas 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 2.1 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).

Table 2.1: 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. (2004a) 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

2.3 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

[4] As Getmansky et al. (2004a), we use a standard MA(k) estimation package (Stata) and transform the resulting estimates by dividing each theta by $1 + \theta_1 + \theta_2$ to satisfy Equation (2.3). In contrast, and also consistent with Getmansky et al. (2004a), we do not impose Equation (2.2) when estimating the thetas and use this restriction as a specification test.

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 (see Appendix A). 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 and keep them for the entire sample period. These risk factors are applied to estimate the following linear multi-factor model to explain the return (R) of each fund i at time t:

$$R_{i,t} - r_{f,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} F_{k,t} + \epsilon_{i,t} \quad t = t_0, \ldots, T \quad i = 1, \ldots, N \tag{2.4}$$

where $r_{f,t}$ is the risk free rate at time t, α_i is the intercept of the regression, $\beta_{i,k}$ reflects the exposures of fund i to the K risk factors F_t at time t and $\epsilon_{i,t}$ is the zero-mean normally distributed tracking error of fund i at time t to the benchmark.

To estimate hedge fund alpha based on a factor model, most papers use either zero investment factors or excess returns of buy and hold factors above the risk free rate.[5] 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 (i.e., the one-month T-bill); 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 at-the-money (ATM) call and

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

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% out-of-the-money (OTM) options, we include ATM options and 7.5% OTM options. We use options that are further out-of-the-money 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 2.2.

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.

We apply two different approaches to estimate the factor loadings and alphas. First, we run standard ordinary least squares (OLS) 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 OLS regressions over 24 months. The statistical significance of the factor loadings and the alpha is estimated based on heteroscedasticity and autocorrelation (HAC)-adjusted standard errors.[6]

2.4 Empirical Analysis

2.4.1 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

[6] 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 with respect to the alpha. If we reduce (increase) the length of the window we report a slightly lower (higher) average alpha.

Table 2.2: 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*	
PTFSCOM**	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*

model. We estimate the alpha on the level of single hedge funds as well as of hedge fund strategy indices.

Table 2.3 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 the average alpha of 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 2.3 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.

Columns '$R^2(adj)$' and '$FH\ R^2(adj)$' in Table 2.3 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. For example, the adjusted r-square of the Emerging Markets index is substantially higher for the stepwise regression model (0.81) as compared to the Fung and Hsieh (2004) model (0.44). The main driver is the inclusion of the MSCI Emerging Markets factor in the former model. The coefficient estimate of this factor is 0.76 indicating a strong long exposure and is highly significant with a t-value of 14.4 for the constant-loading OLS approach. The coefficient values and t-values are similar for the rolling-window approach (0.67 and 13.6) when averaged over time. As a consequence, the alpha based on the two alternative models differs as well and is higher for the stepwise regression model irrespective of whether estimated in a constant-loading or rolling-window regression. In contrast, for the Managed Futures strategy, the alphas and r-squares resulting from the two alternative models are qualitatively similar. This is not surprising as the factors chosen by the stepwise regression approach are largely overlapping with those from the Fung and Hsieh (2004) model and include all three trend following risk factors which show up highly significant in all regressions. 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. Overall, for certain hedge fund strategies, the larger set of risk factors to choose from in a stepwise regression model approach seems to substantially increase explanatory power (e.g., Emerging Markets, Convertible Arbitrage), while for others the explanatory power of the two models is virtually identical (e.g., Dedicated Short Bias, Long/Short Equity Hedge). The effect on alpha resulting from the two alternative models, however, is often very small even when the explanatory power largely differs (e.g., Convertible Arbitrage, Equity Market Neutral). In general, we find qualitatively similar results based on both factor models throughout the chapter.

Unlike Table 2.3, where the alphas are estimated based on the indices for each strategy, Table 2.4 reports the average alpha of all single funds within a strategy. As we have a highly unbalanced panel, the results in Table 2.4 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 2.3, Table 2.4 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 2.4 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).

As in Table 2.3, the results in Table 2.4 show that the stepwise regression model exhibits substantially higher r-squares for certain strategies as compared to the Fung and Hsieh (2004) model. For example, the average r-square for the Convertible Arbitrage funds more than doubles from 0.14 to 0.37. An investigation of the factor loadings of the constant-loading OLS estimation reveals that on average, the funds exhibit a positive and significant exposure to the ML Convertible Bond factor of 0.67 with a t-value of 2.23 as well as a negative exposure of -0.29 to the Russel 3000 (t-value of -2.35). Furthermore, on average, the Convertible Arbitrage funds have a positive and significant exposure of 0.44 to the CS High Yield Index II (t-value of 2.28). All the results are qualitatively identical for the rolling-window approach when averaged over time. The only risk factor the two factor models have in common is the long exposure to Credit Risk (the change in Baa Spread) with t-values of -1.63 and -1.51 for the Fung and Hsieh (2004) model and the stepwise regression approach, respectively.

Another example of a strategy with remarkably different results emerging from the two alternative factor models is Long/Short Equity Hedge. Based on the stepwise regression model we report average alphas of zero and two basis points for the constant-loading and the rolling-window approach, respectively. In contrast, the alphas from the Fung and Hsieh (2004) model amount to 15 and 27 basis points per month. We first check whether these differences are due

Table 2.3: 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. (2004a). 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 2.4: 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. (2004a). 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					N	Nt	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}			(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

to outliers in the cross-sectional alpha distribution resulting from the two alternative factor models. However, while we find a slightly more negatively skewed and leptokurtic alpha distribution for the stepwise regression approach as compared to the Fung and Hsieh (2004) model, there are no obvious outliers resulting from one or the other approach which may be responsible for the qualitative difference in alphas. The higher explanatory power and lower alpha resulting from the stepwise regression approach seems to be mainly due to the inclusion of the momentum and MSCI Emerging Markets factors, which both exhibit positive exposures. Hence, the factors chosen in the stepwise regression model seem to better reflect the investment universe available to Long/Short Equity Hedge managers and therefore provide a benchmark which is more difficult to beat. As in Table 2.3, however, we find for the majority of hedge fund strategies qualitatively similar results based on both factor models.

When comparing the results in Tables 2.3 and 2.4, 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 2.4 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 2.5 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 2.3, 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. (2004a) 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

Table 2.5: 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. (2004a).

	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

Convertible Arbitrage) as compared to strategies investing in highly liquid assets (e.g., Managed Futures). In fact, when replicating Table 2.5 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., 2004a). 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.[7]

For the majority of analyses in this chapter 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).

[7] In unreported tests, we reestimate Table 2.5 based on value-weighted indices. In general, however, the results remain qualitatively unchanged and therefore are not reported in a separate table.

However, we find that the choice of the index does only have a small impact on our results. Overall, the average monthly alpha based on the value-weighted indices for each strategy 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.

2.4.2 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 also 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.[8] Finally, we find a fourth break in August 2007 after the liquidity shock in the financial industry.[9] Khandani and Lo (2010) 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

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

[9]August 2007 can be considered as the start of the recent liquidity crisis of 2008. During August 2007 the spread between the 3-month USD Libor and the 3-month overnight index swap (OIS) rate increased from 12 to 74 basis points.

Table 2.6: 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. (2004a). 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 2.6 — 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

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 2.6 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 2.6). 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.[10] Therefore, beyond the end of the sample of Fung et al. (2008), we do not observe a reduction of hedge fund alpha over time.

Figure 2.1 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.

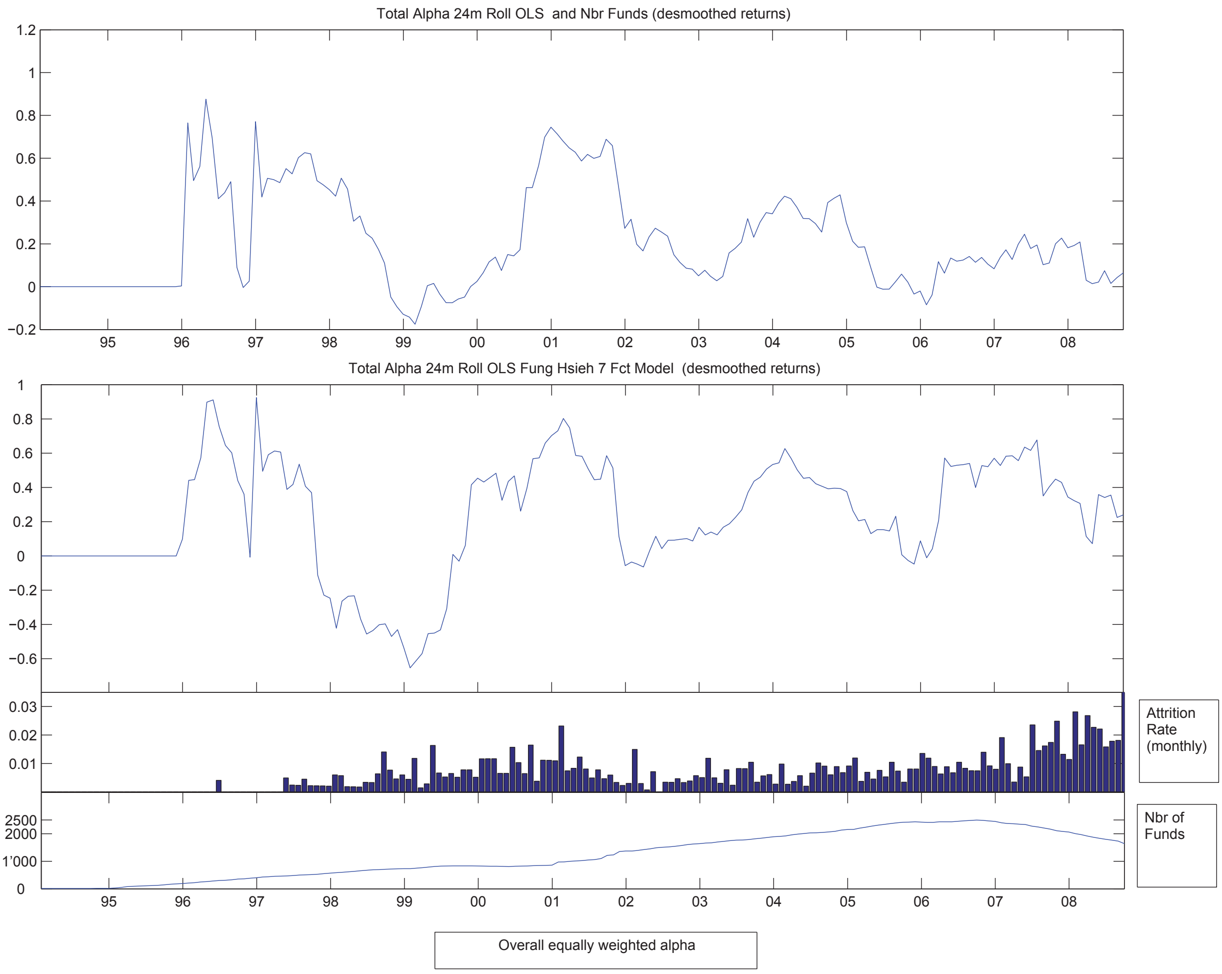
Figure 2.1 shows that both factor models lead to qualitatively very similar results. However, the model based on stepwise regression yields a slightly lower alpha (the overall mean alpha based on stepwise regression amounts to 9bps and 23bps based on the Fung and Hsieh (2004) seven-factor model). The average alpha based on both models is almost always positive. In unreported results, we break down Figure 2.1 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.[11] This is likely to be caused by the lack of a Emerging Markets risk factor in the Fung and Hsieh (2004) model.

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 average monthly alpha on the monthly attrition rate with different leads and lags. We alternatively define the attrition rate as the percentage of funds disappearing from the sample in each month and the percentage of assets under management associated with these funds, respectively. For both alternative measures of the attrition rate and all leads of up to three and all lags of up to

[10] The HAC-adjusted t-value of the alpha for funds of funds increases from 1.8 to 2.2, if only the period subsequent to their sample, i.e., January 2005 to July 2007, is considered.

[11] These results are available upon request.

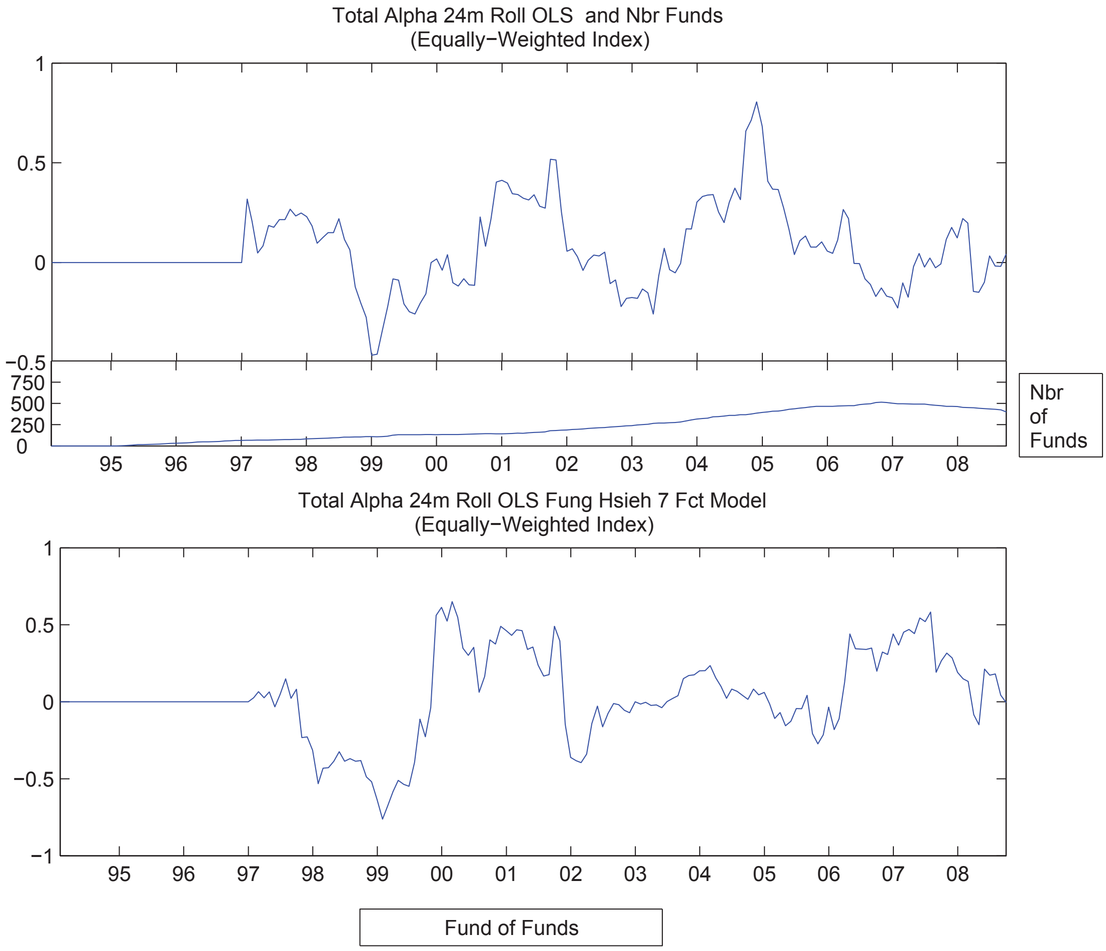
Figure 2.1: Alpha over all hedge fund strategies and over time
This figure shows the average alpha of all hedge funds in our sample based on the stepwise regression factor model (top part) and based on the Fung and Hsieh (2004) seven-factor model (bottom part). The bottom part of the figure additionally 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. (2004a) and we require 24 non-backfilled observations for a fund to be included in this figure.



six months, we find a negative relationship between the attrition rate and the average alpha. All coefficients on the leads and lags are significant at the 5% level or better. The highest significance level (p-value of 0.1%) is found for a four-month lagged attrition rate, when the attrition rate is calculated in terms of assets under management. Hence, we find the attrition rate in general to be 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 6% of the future alphas.

To compare our results with those of Fung et al. (2008), we report the alpha of the equally-

Figure 2.2: 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 additionally 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. (2004a) and we require 24 non-backfilled observations for a fund to be included in this figure.



weighted index of funds of funds separately in Figure 2.2. 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 2.2 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 2.2 are qualitatively similar. The results obtained beyond the end of the sample of Fung et al. (2008) fail to support their finding of a decreasing alpha over time for funds of funds.[12]

2.4.3 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 lose their ability to generate a statistically significant alpha in the 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, their 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

[12] 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 'lose' the first non-backfilled observations of each fund.

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 ($AuM_{i,t}$) and the monthly returns ($r_{i,t}$):

$$F_{i,t} = \frac{AuM_{i,t} - AuM_{i,t-1}(1 + r_{i,t})}{AuM_{i,t-1}} \tag{2.5}$$

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 2.7, 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. Hence, the results based on our entire sample period do not support 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.[13]

Summarizing, we find evidence in support of capacity constraints at the single hedge fund level in the first sub-period from 1996 to 2001. This finding is consistent with Fung et al. (2008). However, the findings based on the more recent sub-sample from 2002 to 2006 contradict those from the first sub-sample. Hence, our results either question the existence of capacity constraints at the single hedge fund level or suggest that the relationship between fund flows and subsequent performance is time-varying.

2.5 Conclusion

This chapter 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.

Unlike previous research, we find no systematically decreasing alpha in the hedge fund industry over time. In addition, we find no evidence pointing to capacity constraints in the hedge fund industry over the full time period from 1996 to 2006. While the findings over the time period from 1996 to 2001 are consistent with Fung et al. (2008) and suggest capacity constraints at the single hedge fund level, the results for the more recent sub-period from 2002 to 2006 suggest a positive relationship between fund flows and future alpha. Consequently, our results suggest

[13] In unreported results, we have also conducted the same analysis with the factor model based on stepwise regression and obtained qualitatively similar results.

that there are either no capacity constraints at the single hedge fund level or that such capacity constraints are time-varying. All these results are qualitatively insensitive with respect to how alpha is measured.

Table 2.7: 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)

Chapter 3

Hedge Fund Characteristics and Performance Persistence

3.1 Introduction

Although a large number of papers have been published on performance persistence of hedge funds, no common consensus has yet been found whether hedge fund performance persists or not. The majority of papers find short-term persistence (e.g., Agarwal and Naik, 2000; Harri and Brorsen, 2004; Manser and Schmid, 2009) but there is only little support for long-term persistence (e.g., Edwards and Caglayan, 2001; Jagannathan et al., 2010). However, in light of notice and redemption periods, the knowledge about short-term performance persistence of hedge funds does not add a great deal of value for an investor.

In this chapter, we therefore focus on long-term performance persistence and attempt to form hedge fund portfolios that consistently outperform their peers. Unlike previous studies, we investigate the performance persistence of two-way sorted portfolios where the sorting is based on past performance and various additional fund characteristics. We use a panel probit regression approach to identify fund characteristics that are significantly related to performance persistence. Moreover, in this study we focus on the investment performance of sorted portfolios instead of investigating the statistical significance of hedge fund performance persistence only. Our results indicate statistically significant and economically substantial performance persistence for time horizons of up to 36 months which can be further improved when a strategy distinctiveness index, which attempts to measure manager skills and the uniqueness of the hedge fund's trading strategies, is used as a second sorting criterion.

In one of the earlier papers on performance persistence, Agarwal and Naik (2000) find evidence for persistence in alpha and the appraisal ratio based on a one-factor model including strategy indices only at quarterly horizons—especially among losers. Capocci and Huebner (2004) report no performance persistence for the best and worst performing hedge funds (as measured by alpha deciles), but for the mediocre performers. Bares et al. (2003) apply a non-parametric approach to individual funds and, alternatively, an eight-factor risk model approach to fund portfolios and find evidence of performance persistence only over one- to three-month horizons. Harri and Brorsen (2004) report short-term persistence over three to four months, with the biggest effect in the first month based on simple regressions of returns on lagged returns. Capocci (2007) proposes an adapted Sharpe ratio, termed "Sharpe score", which divides the return of a fund by a risk figure that takes not only variance into consideration but also skewness and kurtosis, weighted with a factor representing an investor's risk aversion. Capocci (2007) then shows that hedge funds with the highest Sharpe score over a three-year period significantly outperform a 10-factor and a 14-factor model over the subsequent year. Boyson (2008) shows that controlling for style is important when analyzing the performance persistence of hedge funds. In addition, she identifies manager tenure as an additional important factor to be included in the factor model used to test for performance persistence. While Boyson (2008) finds no evidence of performance persistence when only common risk factors are accounted for, she reports persistence at the quarterly time horizon when manager tenure is accounted for. Performance persistence is strongest for young managers with a positive alpha in the past. Fung et al. (2008) investigate the relationship between performance persistence and fund flows for funds of hedge funds. When controlling for fund flows on a single fund level, they find that funds with positive and significant alpha in the past are less likely to achieve a positive and significant alpha in the future when they experience above median capital inflows. They argue that this finding indicates capacity constraints at the single hedge fund level. Manser and Schmid (2009) investigate the performance persistence of equity long/short hedge funds. They report persistence in the alpha from a Carhart (1997) four-factor model and in the Sharpe ratio for time horizons of up to one year and for the worst performing funds also on the biennial horizon.

Based on a six-factor model, Edwards and Caglayan (2001) find one- and two-year alpha persistence for winners and loser hedge funds. Kosowski et al. (2007) use a seven-factor model and apply a bootstrap procedure as well as Bayesian measures to estimate hedge fund performance. When investigating performance-ranked portfolios, they find performance persistence over a one-year horizon. Jagannathan et al. (2010) find even evidence for three-year alpha persistence, based on a three-factor model including the market excess return and two style indices, among well performing funds but no persistence among poorly performing funds. A recent overview of the literature on performance persistence of hedge funds is provided by Eling (2009). He concludes that the lack of consensus in the literature is rather due to differences in the methodological approach used to test persistence than to the measure of performance used.

In this chapter, we investigate the performance persistence of hedge funds over time horizons between 6 and 36 months based on a merged sample from the Lipper/TASS and CISDM databases for the time period from 1994 to 2008. We attempt to improve performance persistence by identifying fund characteristics that are related to the probability of observing performance persistence. We estimate panel probit regressions of an indicator variable for whether a fund exhibits performance persistence on a number of fund characteristics. The fund characteristics we include in this analysis are fund size, fund age, relative fund flows, a dummy variable whether the fund is closed to new investments, two variables related to a fund's liquidity, i.e., the length of the notice and the length of the redemption period, management and incentive fees, leverage, and a dummy variable for whether the fund management is personally invested in the fund. Moreover, we use a 'Strategy Distinctiveness Index' (SDI) as originally suggested by Wang and Zheng (2008), defined as one minus the r-square of a fund's 24 monthly historical returns regressed against an equally-weighted strategy index. As funds within a certain strategy may exhibit more dispersion in SDI than funds within other strategies, we control for such strategy-effects by standardizing the SDI by subtracting the average SDI within the same strategy and dividing by the standard deviation of SDI within this strategy. The SDI measures the percentage of total variance in fund returns that cannot be explained by the returns of its peers. Hence, the higher SDI, the more distinctive, and presumably the more successful, is the fund's investment strategy. Wang and Zheng (2008) show that this index is a good predictor for the future performance of a fund. Consistently, Titman and Tiu (2008) find that hedge funds with a lower r-square from a stepwise based factor model over the last 24 months outperform in terms of raw returns and Sharpe ratios. Moreover, they find performance persistence in Sharpe ratios over one year horizons for these hedge funds.

The study closest to ours is Kumar (2008) who also investigates whether certain fund characteristics are significantly related to hedge fund performance persistence. Kumar (2008) hypothesizes that superior (lower) manager skill is expected to be associated with better (worse) performance in any given period (see also Wang and Zheng, 2008). She uses fund size, fund age, as well as management and incentive fees as proxies for manager skill and hypothesizes that larger and older funds as well as funds with higher fees are indicative of higher manager skills. Consistent with her hypotheses, she finds all these characteristics to be positively related to performance persistence. We carry the analysis in Kumar (2008) at least two steps further. First, we use a fund characteristic that specifically and more directly measures the fund manager's skills. Second, we do not only assess the statistical but also the economic significance of performance persistence. In fact, consistent with Kumar (2008), we find many fund characteristics to be significantly related to performance persistence. However, only one of the 15 characteristics we consider, the SDI, significantly increases the returns of investment strategies based on past performance and such additional fund characteristics.[1]

We investigate performance persistence based on the portfolio approach of Hendricks et al. (1993), which has been used to analyze performance persistence of mutual funds by Carhart (1997), for example. Instead of forming portfolios only based on past performance, we use two-way sorts and additionally use the fund characteristics identified as "persistence-enhancing" in the probit regressions. The performance of these sorted portfolios is then tested out-of-sample over the subsequent period. After each tracking period the sorting procedure is repeated. To assess hedge fund performance, we use two alternative alphas to ensure the robustness of our results with respect to the choice of the factor model. The first alpha is based on a factor model in which we select the risk factors based on a stepwise regression approach. The second alpha is based on the widely used seven-factor model proposed by Fung and Hsieh (2004).

We attempt to carefully account for the various biases in hedge fund data. We eliminate a survivorship bias by including live and dead funds in our sample and restricting the sample period to the post-1993 period, when both TASS and CISDM started to keep all hedge funds which stopped reporting in the database. As TASS provides information on when funds actually started to report to the database, we are able to eliminate the backfill bias for a large part of our sample by deleting all backfilled observations. For funds included in CISDM only, we follow common practice and delete the first 12 observations. Most importantly, we use the approach suggested by Getmansky et al. (2004a) to transform the presumably smoothed, serially correlated returns in our two databases into the unobserved (or "true") desmoothed returns. This is particularly important for studies investigating performance persistence as positive serial correlation will increase the observed persistence.

The results from the probit analyses show that all fund characteristics we consider are significantly related to the probability of observing performance persistence. The coefficients on all fund characteristics, however, exhibit opposite signs for winner and for loser persistence. Hence, the direction of the correlation runs in opposite directions for the performance persistence of well

[1] In addition, we use a more comprehensive factor model to assess alpha, more fund characteristics, and investigate persistence over longer time horizons.

performing and the persistence of poorly performing hedge funds. SDI, fund size, relative fund flows, the length of the notice and the redemption period, a dummy variable whether the fund is closed to new investments, and management and incentive (for the 12-month horizon only) fees are all positively while fund age is negatively related to the probability of observing positive (i.e., winner) performance persistence and vice versa for negative (i.e., loser) performance persistence. When we regress hedge fund alpha on the very same fund characteristics, we find the characteristics that are positively related to winner persistence also to be positively related to alpha—with two exceptions (whether the fund is closed to new investments and incentive fees for the SW alpha).

When assessing performance persistence based on the portfolio approach of Hendricks et al. (1993), we find a statistically and economically significant performance persistence for time horizons of up to 36 months. The difference in monthly alpha based on a stepwise regression model between the quintile-portfolio consisting of the historically best performing hedge funds and the quintile-portfolio consisting of the historically worst performing hedge funds amounts to a statistically significant and economically sizeable 2.80% monthly alpha for 6-month rebalancing horizons, 2.29% for 12-month rebalancing horizons, 1.61% for 24-month rebalancing horizons, and 0.99% for 36-month rebalancing horizons. We then attempt to improve performance persistence by using two-way sorted portfolios based on historical performance and fund characteristics identified to be positively correlated with persistence in the probit regressions. However, we find the SDI to be the only fund characteristic with the ability to systematically improve performance persistence. Over the 6-month horizon the difference in monthly alpha increases to 3.10% when using the SDI as a second sorting criterion (an increase in alpha of 0.30% per month or 3.60% p.a.), over the 12-month horizon to 2.62% (an increase in alpha of 0.33% per month or 3.96% p.a.), and over the 24-month horizon to 1.80% (an increase in alpha of 0.19% per month or 2.28% p.a.). Over the 36-month horizon, SDI does not positively contribute to portfolio returns anymore. These results are robust to various changes in the test specifications including the factor model on which alpha is based, changing the order of the sorting criterions in the two-way sorts, alternative definitions of the SDI variable, and the quantiles used to form portfolios (i.e., median, tercile, quartile, and quintile). Only during the credit crisis of 2008, the positive contribution of the SDI disappears indicating that high-SDI funds may take on larger idiosyncratic risks that show up in lower returns during crisis periods.

The remainder of the chapter is organized as follows. Section 3.2 describes the dataset and variables and explains our methodological approach to assess performance persistence. Section 3.3 presents the results from the empirical analyses and Section 3.4 concludes.

3.2 Data and Variables

3.2.1 Sample Selection and Data

We use a merged sample combining the hedge funds included in the Lipper/TASS and the CISDM databases covering the time period from January 1994 to December 2008. We first clean our sample for duplicate entries of specific hedge funds within each individual database (e.g., due to multiple share classes and onshore and offshore vehicles of some funds). Second, we use a matching algorithm based on fund names, the strategy classification, and return correlation to remove duplicate entries resulting from merging the two databases. We attempt to minimize the survivorship bias by including live and dead funds in our sample and restricting the sample period to the post-1993 period, when both TASS and CISDM started to keep all hedge funds which stopped reporting in the 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 stemming from the TASS database. For the remaining 5% of the funds from the TASS database as well as for all funds from the CISDM database, we follow common practice and delete the first 12 return observations (e.g., Fung and Hsieh, 2000; Edwards and Caglayan, 2001).[2]

As we estimate alpha based on rolling 24-month window regressions, we require at least 24 non-backfilled return observations for a fund to be included in our analysis.[3] 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-month history of returns, and find it to be very small.[4] Furthermore, we exclude fund of hedge funds, hedge funds denoted in a currency other than USD, and funds whose assets under management do not exceed USD 5 millions at

[2] The backfill bias in our sample, calculated as difference in the return of the equally-weighted portfolio of all return observations and the portfolio that only includes non-backfilled returns, amounts to 3.2 basis points per month. For the strategy-indices, this amount varies between 0.9 basis points (Funds of Funds) to 20.2 basis points (Emerging Markets). This compares to Fung and Hsieh (2000) who find a monthly bias of 11.7 basis points for hedge funds and 20 basis points for CTAs over the period 1989 to 1997. Malkiel and Atanu (2005) calculate the backfill bias by comparing the average backfilled hedge fund return with the average non-backfilled return. They report a monthly backfill bias of 61 basis points per month for the period 1994 to 2003. This compares to 38 basis points in our sample or 44 basis points if the same period is considered.

[3] When investigating 36-month performance persistence, we require at least 36 non-backfilled return observations for a fund to be included in our analysis.

[4] In robustness checks, we alternatively require at least 36, 48, or 60 non-backfilled return observations. The number of hedge funds in our sample decreases to 3,366, 2,635, and 2,051 funds, respectively. However, our results remain qualitatively unchanged while all portfolio returns increase by approximately two to three basis points per additional year of return data we require. This finding is consistent with the multi-period sampling bias results in Fung and Hsieh (2000).

least once during their non-backfilled observations.[5] After all these adjustments, we are left with a sample of 4,311 hedge funds with total assets under management of USD 403bn.[6]

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, we follow the same approach as in Chapter 2 and desmooth the return series of our sample as suggested by Getmansky et al. (2004a).[7]

3.2.2 Performance Measurement

In order to control for the funds' systematic risk exposures, we focus on performance persistence in alpha.[8] While there is 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 low, while still being able to appropriately describe the investment opportunities available to hedge funds. We follow Agarwal and Naik (2004), Titman and Tiu (2008), and Ammann et al. (2010a) and use the same forward stepwise regression approach for the selection of the risk factors to be included in our factor models as laid out in Section 2.3 of Chapter 2. We employ the identical risk factors for all funds within a strategy and keep them for the entire sample period. The complete set of factors considered for the selection procedure is listed in Appendix A and choice of factors resulting from the stepwise procedure for each strategy for the sample used in this chapter is reported in Table 3.1. Henceforth, we label this alpha based on the stepwise regression approach 'SW alpha'.

[5] We exclude fund of hedge funds from our sample as SDI is no meaningful measure of strategy distinctiveness for them (e.g., see Wang and Zheng, 2008). Including fund of hedge funds in our analysis does not qualitatively change our results. However, as expected, the increase in performance persistence attributable to additionally sorting for SDI is limited (and at the strategy level the second lowest after fixed income arbitrage).

[6] According to the TASS Asset Flow Report of Q4, 2009 the hedge fund industry amounted to an estimated USD 1,210bn at the end of 2008 (excluding funds of funds). Our sample therefore covers roughly one third of the total assets under management of the industry.

[7] Jagannathan et al. (2010) and Ammann et al. (2010a) find that this procedure of desmoothing the returns leads to a reduction of hedge fund alpha.

[8] Alternatively, we also investigate the persistence in raw-returns.

Table 3.1: Factor selection for each hedge fund strategy
The table reports the factors selected from a forward stepwise regression approach applied to equally-weighted strategy indices comprising our sample funds within each strategy. These risk factors are selected from 23 potential risk factors. The full choice of factors is provided in Appendix A. We require significance at the 5% level for factors be included (and 10% to remain) in the regression models.

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

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. The alpha based on the Fung and Hsieh (2004) seven-factor model is henceforth termed 'FH alpha'.

One major concern with the stepwise regression approach is that the methodology is prone to data mining and may lead to an over-fitting in the in-sample period while performing very poorly out-of-sample. We test the out-of-sample performance of our stepwise regression models by comparing the average r-square obtained in alpha regressions over the second half of our sample period (the 90 months from July 2001 to December 2008) using the risk factors obtained in stepwise regressions run either for the first sample half (January 1994 to June 2001) or stepwise regressions run for the second half of our sample period (July 2001 to December 2008). Hence, we compare the r-square obtained in out-of-sample regressions to those from in-sample regressions where the stepwise approach was run over the same sample period as the subsequent alpha regressions. We do this on the strategy level and aggregate the results over all 10 strategies. Most importantly, over all strategies, we find an average in-sample r-square of 0.724 that compares to an out-of-sample r-square of 0.666. Hence, the average out-of-sample r-square is reasonably high and only slightly reduced as compared to the in-sample r-square. For comparison reasons, the average r-square from the FH model over the same time period is substantially lower than both the in-sample and the out-of-sample r-square from the stepwise models (0.507). This result also holds at the strategy level with two exceptions. For Dedicated Short Bias and Fixed Income Arbitrage the r-square from the FH model is smaller than the in-sample but larger than the out-of-sample r-square from the SW model. However, in both cases all three r-squares are very similar (Dedicated Short Bias: 0.874, 0.879, 0.913; Fixed Income Arbitrage strategy: 0.602, 0.608, 0.659).

Finally, we investigate which factors chosen in our stepwise regressions and not included in the Fung and Hsieh (2004) seven-factor model are responsible for the differences in the model fit between the SW regressions and the FH regressions. When comparing the factor choice (as reported in Table 3.1) and level of significance in the SW factor model to the seven FH factors and their significance, we find substantial differences for some of the strategies. To save space, we do not report the results in a table and concentrate on the three strategies that exhibit the largest differences in adjusted r-squares when applying the two alternative factor models to the strategy index. These are the strategies Equity Market Neutral (r-square of 47.0% vs. 21.4%), Global Macro (35.4% vs. 18.8%), and Emerging Markets (80.4% vs. 44.5%). For the Equity Market Neutral strategy, the SW approach chooses the following five factors, none of which is included in the seven FH factors: momentum factor, 92.5% ATM put option on the S&P 500 index, 107.5% OTM call option on the S&P 500 index, high yield bond index, and the return of a stock-based primitive trend following strategy. All these factors are significant at the 1% level while of the seven FH factors only the bond and the S&P 500 return factors are significant at the 10% and 1% level, respectively. For the Global Macro strategy, the SW approach selects the following five factors: 3m TED spread, world government bond index, MSCI emerging markets index, the return of a currency-based primitive trend following strategy, and the momentum factor. Only the last factor, the return of a currency-based primitive trend following strategy, is among the seven FH factors. Again all five factors are significant at the 1% level while in the FH model only three factors are significant at the 1% level (the currency-based primitive trend following strategy, the S&P 500 total return, and the monthly change in the 10-year treasury constant maturity yield) and one other factor at the 10% level (SMB). Finally, for the Emerging Markets strategy, the SW approach selects the following three risk factors: momentum factor, MSCI emerging markets factor, and dollar index spot factor. Again, all three factors are significant at the 1% level, not surprisingly with the highest significance level for the emerging markets factor (t-value of 13.85%). Of the seven FH factors only two are significant (also at the 1% level), the S&P 500 total return and SMB. Hence, for many strategies, we find substantial differences in the factor choice between the SW and FH models, whereas some the most highly significant, and economically (as well as intuitively) meaningful factors are missing in the SW model. For other strategies, however, the average adjusted r-squares (and the choice of the risk factors) are much more similar between the two risk models, examples being Managed Futures (r-square of 38.8% vs. 32.0%) and Long /Short Equity (89.6% vs. 79.6%).

3.2.3 Measuring Performance Persistence

We classify a fund to exhibit performance persistence if it is a winner (or a loser) in two subsequent non-overlapping time periods. A fund is classified as being a winner (loser) if it exhibits an above-median (below-median) alpha in the respective time period.[9] Time periods used include 6 months as well as 1, 2, and 3 years. We test the robustness of the results by alternatively using alphas based on both, our stepwise regression approach and the FH factor model.

Next, we attempt to identify fund characteristics which are correlated with the funds' performance persistence. We do this by estimating panel probit regressions of an indicator variable

[9] In robustness checks, we also use higher quantiles than the median to classify funds as winners or losers including the 70%/30% and 80%/20% quantiles.

for whether a hedge fund exhibits performance persistence (1) or not (0) on a number of fund characteristics. We use three alternative specifications of this performance persistence dummy variable. The first variable, WL, equals one for all fund-months for which the fund is either a winner or a loser in two subsequent non-overlapping time periods and zero otherwise. The second specification, WW, measures only the persistence of winner funds and thus is equal to one for all fund-months for which the fund is a winner in two subsequent non-overlapping time periods and zero otherwise. The third specification, LL, measures only the persistence of loser funds and is equal to one for all fund-months for which the fund is a loser in two subsequent non-overlapping time periods and zero otherwise.

Finally, each period, we form portfolios not only based on past performance but additionally on the fund characteristics identified as "persistence-enhancing" factors in the probit regressions. The performance of these sorted portfolios is then tested out-of-sample in the next period. After each tracking period the sorting is repeated. We calculate the alpha of each fund within a portfolio and apply equal weights. A similar portfolio approach has been used in the mutual fund literature by Hendricks et al. (1993) and Carhart (1997).

The first fund characteristic we use as explanatory variable in the probit regression is the Strategy Distinctiveness Index (SDI) as originally suggested by Wang and Zheng (2008), defined as $(1 - R^2)$, using the r-square of a fund's 24 monthly historical returns regressed against the equally-weighted strategy index. SDI measures the percentage of total variance in fund returns that cannot be explained by the returns of its peers. The higher the SDI, the more distinctive, and presumably the more successful, is the fund's investment strategy. If hedge funds within a certain strategy exhibit more dispersion than within other strategies, the funds in our sample with a high SDI value may have a disproportional tilt towards this strategy. Therefore, the performance difference associated with SDI may be driven rather by the funds' strategy than their distinctiveness. Hence, we standardize the SDI within each strategy by subtracting the average SDI within the same strategy and dividing by the cross-sectional standard deviation in SDI within this strategy. Wang and Zheng (2008) show that this index is a good predictor for the future performance of a fund.

In various robustness tests, we use alternative versions of SDI. To mitigate the well known problem of erroneous strategy classifications in the commercial hedge fund databases due to self-reporting by the funds, we alternatively calculate SDI against the highest correlated strategy index instead of the self-declared strategy index. Following Titman and Tiu (2008), who argue that better informed hedge funds choose less exposure to systematic factor risk, we alternatively calculate SDI against the stepwise regression model. Furthermore, we alternatively define SDI as the r-square from a regression of the funds' returns on the returns of the funds' self-declared strategy index and the returns of an index of all hedge funds in our sample. Finally, we also use the alternative SDI measure proposed by Sun et al. (2009), a revised version of Wang and Zheng (2008), which is defined as one minus the correlation of the individual hedge funds' returns with the average returns of their peer funds with the same strategy classification. This SDI ranges between 0 and 2 in theory.

The second fund characteristic we use is lagged fund flows. Fung et al. (2008) investigate the relation between alpha and lagged fund flows on an individual fund of fund level and conclude that funds which generated a statistically significant alpha in the past and experience above-median capital inflows, are more likely to lose their ability to generate a statistically significant alpha in the future.[10] To calculate lagged fund flows, we follow a similar approach as Naik et al. (2007), Fung et al. (2008), and Titman and Tiu (2008) and compile the annual relative net fund flows for each fund-month observation. 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 ($AuM_{i,t}$) and the monthly returns ($r_{i,t}$):

$$F_{i,t} = AuM_{i,t} - AuM_{i,t-1}(1 + r_{i,t}) \tag{3.1}$$

Capital inflows are treated as if they were received at the end of each month. For the calculation of the annual relative net fund flows ($FF_{i,t}^{rel}$), the monthly absolute fund flows are aggregated and calculated in relation to the assets under management of each fund ($AuM_{(i,t-12)}$) one year earlier:

$$FF_{i,t}^{rel} = \frac{\sum_{t=-1}^{-12} F_{i,t}}{AuM_{i,t-12}} \tag{3.2}$$

Finally, we winsorize the relative yearly fund flows at the 1% tails to account for extreme observations.

Further, we include a number of fund characteristics in our probit regressions that are related to a fund's liquidity. Aragon (2007) finds that the positive and significant alpha of hedge

[10] Ammann et al. (2010a) confirm these findings using single hedge funds over the same time period as Fung et al. (2008) but find contradicting evidence when using a longer sample period.

funds disappears after controlling for lockup restrictions, notice period length, and minimum investment size. He therefore interprets the abnormal average return as a liquidity premium. The liquidity-related variables we include in our regressions include the natural logarithm of the notice period length (in number of days), the natural logarithm of the redemption period length (in number of days)[11], and a dummy variable whether the fund is closed to new investments.[12] Finally, we include fund size as measured by the natural logarithm of assets under management and fund age as measured by the natural logarithm of the months a fund existed (or the number of months a fund reported its returns in case the inception date is unknown). As it is common in the literature, we use fund age also as proxy for manager experience (e.g., Boyson, 2010). In general, it is assumed in the hedge fund literature that the same manager stays with a fund over its entire fund life and Boyson (2010) provides empirical support for this conjecture.

3.3 Empirical Analysis

3.3.1 Fund Characteristics and Performance Persistence

In Table 3.2, we investigate the relationship between various fund characteristics and the performance persistence of single hedge funds. The dependent variable is a dummy variable which is equal to one if a fund is a winner (loser) fund in two consecutive, non-overlapping time periods of 12 months (Columns 1 to 3), 24 months (Columns 4 to 6), and 36 months (Columns 7 to 9). Winner (loser) funds are defined as funds which exhibit an above-median (below-median) alpha based on the stepwise regression model. We use three alternative specifications of the dependent variable, the first summarizing performance persistence of both winners and losers (Columns 1, 4, and 7), the second only indicating winner persistence (Columns 2, 5, and 8), and the third measuring loser persistence only (Columns 3, 6, and 9). As the dependent variable is binary (a value of one indicates performance persistence and a value of zero no persistence), we estimate probit regressions.[13] In all regressions we include time and strategy fixed effects and the full

[11]If a fund labels its redemption frequency to be 'other' than the categories provided by the databases (which end at triennial), we assign a value of 1,048 days (four years in terms of trading days).

[12]In unreported robustness tests, we additionally use the natural logarithm of the length of the lockup period and the length of the subscription period. However, these variables are estimated to be insignificant in most specifications and add very little explanatory power to the models.

[13]In unreported robustness tests, we alternatively use linear panel regressions including time and strategy fixed effects with cluster robust standard errors (where the clustering is at the single hedge fund level) and Fama and MacBeth (1973) regressions with heteroscedasticity and autocorrelation consistent standard errors. However, the results based on all these alternative estimation procedures are very similar and remain qualitatively unchanged.

set of control variables including the strategy distinctiveness index (SDI), fund size (Ln(AuM)), relative fund flows (Relative fund flows), fund age (Ln(fund age in months)), the length of the notice period (Ln(notice days)), the length of the redemption period (Ln(redemption days)), a dummy variable whether the fund is closed to new investments (Closed to investment), and management (Management fee) and incentive fees (Incentive fee).

The results on 12-month persistence in Columns 1 to 3 of Table 3.2 show that the coefficients on all explanatory variables exhibit the opposite sign for winner (Column 2) and loser persistence (Column 3). Moreover, the coefficients on all explanatory variables are significant at the 1% level for both winner and loser persistence. As a consequence of the inverse signs for winners and losers, the significance of the coefficients is substantially reduced in Column 1, where winner and loser persistence is investigated jointly. Hence, while the same factors are significantly related to both winner and loser performance, the direction of this correlation is diametrically opposed for winners and losers. Most importantly, we find a positive and highly significant coefficient on SDI for winner persistence indicating that funds with a high SDI, i.e., funds with skilled managers following proprietary trading strategies, are more likely to be persistent winner funds. This finding is consistent with Wang and Zheng (2008). In contrast, the coefficient on SDI is negative and highly significant for loser persistence indicating that funds with a high SDI are substantially less likely to be persistent underperformers as compared to funds with a low SDI. Moreover, winner persistence is significantly positively related to fund size, relative fund flows, the fund illiquidity as measured by the length of the notice and redemption periods, and management and incentive fees. Further, the negative coefficient on Ln(AuM) indicates that smaller funds are more likely to be persistent winners. This finding is consistent with a recent study by Aggarwal and Jorion (2010) who show that young and emerging funds exhibit strong performance persistence. Finally, funds closed to new investments are more likely to be persistent winners.

For the longer time horizons of 24 (Columns 4 to 6) and 36 months (Columns 7 to 9), we find qualitatively similar results with no change in signs or the level of significance for both winner and loser persistence (with two exceptions: the coefficients on the incentive fee variable turn insignificant in Columns 5 and 8). However, the magnitude of the t-values somewhat decreases in the length of the time period over which persistence is measured but all coefficients remain significant at the 1% level. In contrast and as expected, the results on the joint persistence of winners and losers in Columns 1, 4, and 7 change—depending on the relative size and significance of the coefficients in the respective winner- and loser-regressions.

Table 3.2: Fund characteristics and alpha persistence

The table reports the results from panel probit regressions of an indicator variable for whether a hedge fund exhibits alpha performance persistence (1) or not (0) on a number of fund characteristics. Alpha is estimated with a factor model that selects the risk factors based on stepwise regression (SW) over rolling 24-month windows. We classify a fund to exhibit performance persistence if it is a winner (or a loser) in two subsequent non-overlapping time periods. A fund is classified as being a winner (loser) if it exhibits an above-median (below-median) alpha based on the stepwise-regression factor model. We label these funds as WW (winner persistence) and LL (loser persistence). WL is the sum of WW and LL and hence combines winner and loser persistence in a joint persistence measure. We investigate performance persistence over non-overlapping time horizons of 12 months (Columns 1 to 3), 24 months (Columns 4 to 6), and 36 months (Columns 7 to 9). All regressions include time and strategy dummy variables (not reported). The table is based on all USD denominated funds included in the CISDM and TASS databases with at least 24 non-backfilled observations. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004a). t-values are reported in parentheses. Besides the pseudo r-square the fraction correctly predicted is reported. The fraction correctly predicted classifies all observations Y_i, for which $Y_i = 1$ and the predicted probability exceeds 50%, and all observations Y_i, for which $Y_i = 0$ and the predicted probability is less than 50%, as correctly predicted. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level.

	WL 12m (1)	WW 12m (2)	LL 12m (3)	WL 24m (4)	WW 24m (5)	LL 24m (6)	WL 36m (7)	WW36m (8)	LL 36m (9)
Constant	0.114	-0.919 ***	-0.268 *	-0.168	-0.999 ***	-0.530 ***	-0.295 *	-1.073 ***	-0.596 ***
	(0.797)	(-6.183)	(-1.749)	(-1.119)	(-6.198)	(-3.089)	(-1.728)	(-5.805)	(-3.085)
SDI	-0.006	0.166 ***	-0.178 ***	-0.001	0.151 ***	-0.159 ***	0.001	0.118 ***	-0.130 ***
	(-1.638)	(39.636)	(-42.470)	(-0.213)	(30.603)	(-31.964)	(0.208)	(17.188)	(-18.680)
Ln(AuM)	-0.002	0.028 ***	-0.030 ***	-0.015 ***	0.019 ***	-0.038 ***	-0.011 ***	0.020 ***	-0.033 ***
	(-0.684)	(10.972)	(-11.539)	(-5.271)	(6.420)	(-12.385)	(-2.811)	(4.797)	(-7.768)
Relative fund flows	0.007	0.077 ***	-0.092 ***	-0.005	0.079 ***	-0.119 ***	-0.047 ***	0.046 ***	-0.139 ***
	(1.627)	(18.064)	(-18.298)	(-1.150)	(16.060)	(-19.457)	(-6.833)	(6.321)	(-15.213)
Ln(fund age in months)	0.006	-0.069 ***	0.074 ***	0.055 ***	-0.087 ***	0.150 ***	0.015	-0.174 ***	0.183 ***
	(0.728)	(-8.201)	(8.709)	(5.856)	(-8.648)	(14.733)	(1.022)	(-10.509)	(11.177)
Ln(notice days)	0.015 ***	0.071 ***	-0.055 ***	-0.000	0.086 ***	-0.087 ***	0.018 ***	0.138 ***	-0.114 ***
	(4.082)	(17.625)	(-13.706)	(-0.058)	(18.011)	(-18.743)	(3.182)	(21.221)	(-18.348)
Ln(redemption days)	-0.009 **	0.037 ***	-0.048 ***	0.021 ***	0.068 ***	-0.044 ***	0.015 **	0.059 ***	-0.045 ***
	(-2.127)	(8.206)	(-10.459)	(4.392)	(13.043)	(-8.341)	(2.358)	(8.646)	(-6.422)
Closed to investment	0.018	0.082 ***	-0.071 ***	0.060 ***	0.167 ***	-0.109 ***	0.039 **	0.150 ***	-0.117 ***
	(1.617)	(7.271)	(-5.942)	(4.854)	(12.894)	(-7.775)	(2.313)	(8.390)	(-6.060)
Management fee	0.014 ***	0.036 ***	-0.029 ***	0.010 **	0.052 ***	-0.069 ***	0.016 ***	0.073 ***	-0.116 ***
	(3.414)	(8.860)	(-5.940)	(2.334)	(11.414)	(-10.493)	(2.895)	(12.027)	(-11.916)
Incentive fee	-0.002 **	0.003 ***	-0.004 ***	-0.005 ***	0.000	-0.005 ***	-0.009 ***	-0.000	-0.009 ***
	(-2.233)	(3.210)	(-4.703)	(-5.721)	(0.482)	(-5.708)	(-7.976)	(-0.176)	(-7.422)
Number of observations	111,646	111,646	111,646	82,978	82,978	82,978	44,300	44,300	44,300
Number of funds	2,734	2,734	2,734	2,099	2,099	2,099	1,219	1,219	1,219
Pseudo R^2	0.48%	2.50%	2.55%	0.62%	3.01%	3.49%	0.81%	3.26%	4.05%
Correctly predicted	58.49%	69.73%	71.89%	55.08%	72.01%	73.94%	55.00%	72.46%	73.88%

We perform a number of robustness tests on these results. First, we extend the set of nine fund characteristics and additionally include a dummy variable for whether the fund management is personally invested in the fund and the funds' average leverage ratio. Both these variables show relatively poor coverage in both the TASS and CISDM databases and reduce the sample size from between 44,300 and 111,646 fund-month observations as reported in Table 3.2 to between 14,188 and 41,834 fund-month observations, a decrease by roughly two thirds. The coefficient on the dummy variable for whether fund management is personally invested in the fund is always positive and significant for winner persistence and negative and significant for loser persistence. The coefficient on the leverage variable is always negative but significant only for winner persistence over the 12- and 36-month horizons.[14] Second, we reestimate all regressions by replacing the dependent variable and using the FH alpha instead of the SW alpha when assessing performance persistence. The results are very similar to those reported in Table 3.2 and therefore not reported in a table for space reasons. Third, we use more restrictive alpha quantiles than the median to classify funds as winners and losers, including the 30% / 70% and the 20% / 80% quintiles. Again we find the results to remain qualitatively unchanged with the exception of the negative coefficient on SDI for loser persistence which turns insignificant for the 36-month horizon. Fourth, we use alternative versions of SDI as explained in Section 3.2.3. The results remain qualitatively identical for all four alternative versions of SDI and are therefore not reported for space reasons. Finally, we investigate the performance persistence of raw returns instead of alphas. Again the results remain virtually unchanged with one important exception: the coefficient on SDI switches signs and is now negative and significant for winner persistence and positive and significant for loser persistence. Hence, the results of the probit regressions on raw returns suggest that funds with a low SDI have persistently high raw returns while the results in Table 3.2 show the these low SDI funds have persistently low alphas. Hence, funds with a low SDI seem to load on large amounts of systematic risk. This is exactly what the SDI attempts to measure: Funds with a high SDI are expected to follow proprietary trading strategies and have less systematic risk while low SDI funds are expected to herd and thereby carry more systematic risk.

3.3.2 Fund Characteristics and Alpha

In this section, we investigate the relation between alpha and the same fund characteristics included in the analysis of alpha persistence reported in Table 3.2. We estimate panel regressions

[14] For space reasons, we do not report these results in a separate table.

of hedge fund alpha on the nine fund characteristics, or sub-sets thereof, and include time and strategy fixed effects. To account for clustering at the fund-level, i.e., the dependence of observations on one specific fund, we use the cluster-robust variant of the Huber-White sandwich estimator. The results are reported in Table 3.3. In Columns 1, 3, and 5, the dependent variable is an alpha based on a stepwise regression approach and in Columns 2, 4, and 6, the dependent variable is an alpha based on the Fung and Hsieh (2004) seven-factor model.

The results from estimating regressions including the full set of nine fund characteristics are reported in Columns 1 and 2. Most importantly, the coefficient on SDI is positive and significant at the 1% level in both specifications. This finding is consistent with Wang and Zheng (2008) and suggests that funds with skilled managers pursuing unique trading strategies exhibit higher alphas than funds with presumably less skilled managers following publicly known trading strategies. The positive and significant coefficient on Ln(AuM) indicates that larger funds exhibit higher alphas. This finding is consistent with Teo (2009) for example. Relative fund flows over the last year are positively related to hedge fund alpha. This finding is consistent with Ammann et al. (2010a) but contradicts Fung et al. (2008). Consistent with Aragon (2007), the two variables related to fund liquidity, i.e., the length of the notice period and the length of the redemption period, are both estimated to be positive and significant (with the exception of Ln(redemption days) which is not significant in Column 2). Hence, we find some evidence of a liquidity premium associated with hedge fund investing. Finally, the coefficient on fund age, the dummy variable whether the fund is closed to new investments, as well as management and incentive fees are all insignificant.

In unreported tests, we additionally include the dummy variable for whether the fund management is personally invested in the fund and the funds' average leverage ratio in the regression equations reported in the first two columns of Table 3.3. However, the coefficients on both of these variables are insignificant in both specifications while the sample size is substantially reduced to 90,802 observations when only the dummy variable for the fund management's investment is included, 87,376 observations when only leverage is added, and 56,710 when both variables are included. Moreover, none of these two variables is selected in the stepwise approach explained below. Therefore, we do not report the results from these extended regression specifications for space reasons.

Table 3.3: Fund characteristics and alpha

The table reports the results from panel regressions of hedge fund alpha on a number of fund characteristics. Alpha is estimated with two alternative factor models. The first factor model selects the risk factors based on a stepwise regression approach (SW). The second factor model is the Fung and Hsieh (2004) seven-factor model (FH). The factor models are estimated based on an OLS estimation over rolling 24-month windows. The table is based on all USD denominated funds with at least 24 non-backfilled observations. All regressions include time and strategy dummy variables (not reported). The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004a). All alphas are expressed in monthly percentage returns. The t-values (in parentheses) are based on the cluster-robust variant of the Huber-White sandwich estimator which accounts for the dependence of observations within clusters (different month-observations for one specific fund). F-tests are performed for the simultaneous significance of all coefficients. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level.

	Alpha SW (1)	Alpha FH (2)	Alpha SW (3)	Alpha FH (4)	Alpha SW (5)	Alpha FH (6)	Alpha SW (7)	Alpha FH (8)
Constant	-0.100	-0.532	0.492 **	0.511 **	-0.330	-0.739 ***	-0.671 ***	-1.028 ***
	(-0.163)	(-1.148)	(2.398)	(2.360)	(-1.222)	(-3.009)	(-4.537)	(-6.268)
SDI	0.227 ***	0.122 ***	0.229 ***	0.121 ***	0.227 ***	0.123 ***	0.202 ***	0.093 ***
	(5.900)	(4.492)	(7.616)	(5.541)	(6.597)	(5.016)	(10.963)	(6.158)
Ln(AuM)	0.062 ***	0.08 ***	0.058 ***	0.072 ***	0.072 ***	0.090 ***	0.063 ***	0.091 ***
	(4.317)	(7.877)	(5.063)	(7.803)	(6.141)	(10.307)	(6.059)	(8.774)
Relative fund flows	0.144 ***	0.153 ***	0.163 ***	0.164 ***	0.147 ***	0.155 ***	0.167 ***	0.164 ***
	(4.733)	(5.675)	(5.951)	(6.982)	(4.304)	(5.311)	(8.01)	(10.784)
Ln(fundage in months)	-0.046	-0.034						
	(-0.562)	(-0.597)						
Ln(notice days)	0.072 **	0.06 **						
	(2.356)	(2.410)						
Ln(redemption days)	0.008	0.004						
	(0.398)	(0.227)						
Closed to investment	0.186	0.154						
	(0.993)	(1.143)						
Management fee	0.150	0.131						
	(1.037)	(1.254)						
Incentive Fee	-0.001	0.002						
	(-0.230)	(0.454)						
Ln(notice and redemptiondays)					0.070 ***	0.057 ***	0.038 **	0.040 **
					(3.167)	(3.119)	(2.061)	(2.226)
24m lagged alpha							0.094 ***	0.013
							(3.307)	(1.556)
Alpha observations	147,841	147,841	191,691	191,691	156,960	156,960	90,931	90,931
Number of funds	3,545	3,545	4,310	4,310	3,756	3,756	3,708	3,708
R^2	2.98%	3.43%	3.13%	3.50%	2.81%	2.99%	4.22%	4.29%
F-test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

In Columns 3 and 4, we use a similar forward stepwise regression approach as for the factor choice when calculating the SW alpha (see Section 3.2.2). The three factors chosen out of a pool of 15 factors are the standard SDI (i.e., calculated against the self-declared strategy), fund size, and relative fund flows.[15] The results are consistent with those in Columns 1 and 2 and show that funds with a high SDI, larger funds, and funds with high relative fund flows have higher alphas on average. All coefficients are significant at the 1% level.

The first factor that was not chosen by the forward stepwise regression approach, or the last one to be dropped by a backward stepwise regression approach, was the natural logarithm of the sum of the notice days and redemption period. Hence, as a robustness check, we additionally include this variable besides the three variables chosen by the stepwise regression approach. While the coefficients on SDI, fund size, and relative fund flows all remain positive and significant at the 1% level, the coefficient on the combined notice and redemption period variables is also positive and significant at the 1% level in both specifications. Hence, we confirm the finding of an illiquidity premium. Moreover, and consistent with Aragon (2007), we show that the positive and significant monthly alphas of 0.49% and 0.51% reported in Columns 3 and 4, turn negative in Columns 5 and 6 when the liquidity-based control variables are included in the regression. After controlling for these trading restrictions, fund performance is reduced by 0.84% and 1.25% and insignificant or even negative and significant. In Columns 7 and 8, we replicate the results in Columns 5 and 6 while additionally controlling for the effect of performance persistence by including an alpha lagged by 24 months. The coefficients on all explanatory variables remain qualitatively unchanged as compared to Columns 5 and 6 while the coefficients on alpha are positive in both specifications (but significant only in Column 7).

3.3.3 Forming persistent Portfolios

In this section, we investigate whether the factors that have been identified to enhance hedge fund performance persistence (and hedge fund alpha) in Section 3.3.1 (Section 3.3.2) allow the construction of hedge fund portfolios that persistently outperform other hedge fund portfolios. We proceed by extending the traditional portfolio-approach to assess performance persistence,

[15] The 15 factors to choose from are: the SDI against the self-declared strategy (and the four alternative definitions of SDI), relative fund flows, fund size, fund age, length of the notice period, length of the redemption period, a dummy variable whether the fund is closed to new investments, management fees, incentive fees, a dummy variable for whether the fund management is personally invested in the fund, and leverage (and alternatively, instead of the length of the notice period and the length of the redemption period, the sum of these two). To mitigate the problem of multicollinearity of the independent variables, only one of the three alternative SDIs and only either the sum of the lengths of the notice and redemption periods or one (or both) of its constituents are allowed to be selected.

as for example used in Hendricks et al. (1993) and Carhart (1997), by forming portfolios not only based on past performance but additionally on the fund characteristics identified as "persistence-enhancing" factors in the probit regressions of Section 3.3.1. The performance of these sorted portfolios is then tested out-of-sample over the subsequent period of 6 to 36 months. After each tracking period the sorting is repeated.[16]

In Table 3.4, we first sort the hedge funds into five sub-portfolios based on the funds' historical 6-month, 12-month, 24-month, and 36-month alphas. Next, the funds within each of these five portfolios are sorted further based on the SDI over the previous 24 months: We divide each of the five alpha-sorted portfolios into two sub-portfolios, one including those hedge funds with an above- and one including those with a below-median SDI. This sorting algorithm ensures an even distribution of the number of hedge funds across portfolios and prevents portfolios from including very few or no funds at all. However, the selection of funds within each portfolio is dependent on the sorting pattern.[17] After each tracking period the sorting is repeated and the portfolio rebalanced. For investigating 6-month performance persistence, the portfolios are rebalanced biannually, annually for 12-month persistence, biennially for 24-month persistence, and triannually for 36-month persistence. The performance of these sorted portfolios, as measured by the FH and SW alpha, is then tested out-of-sample in the next non-overlapping 6-month, 12-month, 24-month, and 36-month period. Panel A reports the results from the analysis of 6-month performance persistence (i.e., sorting based on 6-month historical alpha, biannual rebalancing, and test of 6-month out-of-sample performance), Panel B, C, and D from the analyses of 12-month, 24-month, and 36-month persistence.

The results on 6-month performance persistence in Panel A of Table 3.4 show that portfolio alphas increase monotonically in both the historical alpha and the SDI. The differences between the portfolios with the highest historical alpha (alpha 5) and the portfolios with the lowest historical alpha (alpha 1) amount to between 2.46% and 3.03% monthly alpha and are all significant at the 1% level for both the SW alpha and the FH alpha as well as the "SDI high" and "SDI low" sub-portfolios. However, the difference between the high- and low-SDI portfolios is insignificant with two exceptions (the alpha 5 and alpha 2 sub-portfolios when using the SW alpha). In the first and fifth columns ('alpha only'), we use a one-way portfolio sort based on historical alpha only and in the last column based on SDI only. Consistent with our expectations and the results in Table 3.2, we find significantly higher returns for the portfolio including hedge

[16] If hedge funds within a portfolio disappear from the sample, we estimate their alpha for the time period until defunct.

[17] Therefore, in a robustness check, we will reverse the order of this sorting procedure.

funds with high SDI as compared to the portfolio including low-SDI funds. The difference amounts to 0.35% monthly alpha and is significant at the 1% level. Moreover, the portfolio alphas increase monotonically in the historical alpha providing strong evidence of performance persistence over a 6-month horizon. The difference in monthly SW (FH) alpha between the portfolio with the highest historical alpha and the portfolio with the lowest historical alpha is 2.80% (2.66%) and significant at the 1% level. Further, consistent with Ammann et al. (2010a) and Titman and Tiu (2008), the results in Panel A show that FH alphas are in general higher as compared to the SW alphas.

To assess whether using two-way sorts based on historical alphas and the SDI as compared to using one-way sorts based on historical alphas only, we need to compare the alphas of the high-alpha/high-SDI portfolios to those of the low-alpha/low-SDI portfolios. In Panel A of Table 3.4, the resulting return differences are 3.10% and 2.77% for the SW and the FH alpha, respectively. The "pure" performance persistence based on one-way alpha sorts is 2.80% and 2.66% as indicated in the first (SW alpha) and fifth (FH alpha) columns of the table. Hence, additionally using SDI as a second sorting criterion increases alphas by 0.30% (0.11%) per month or 3.60% (1.32%) per annum. Hence, while a one-way sorting procedure based on historical SW and FH alpha already generates a very high difference in alpha of monthly 2.88% and 2.66% between the high- and low-alpha portfolios, an additional sorting based on the SDI allows to further increase this difference in alpha.

Average adjusted r-squares of all funds of a portfolio are reported in square brackets for each of the five alpha-sorted portfolios as well as for the 10 alpha and SDI two-way sorted portfolios.[18] The r-square values are remarkably constant across the different alpha-sorted portfolios but show large differences between the SDI-sorted portfolios. Specifically, the r-squares of the low-SDI portfolios are substantially higher than those of the high-SDI portfolios. This finding is expected as the SDI is defined as one minus the r-square of a fund's 24 monthly historical returns regressed against an equally-weighted strategy index. If the strategy index is positively correlated to the majority of risk factors included in the two alternative factor models, which can be expected (and is observed in unreported tests), a high SDI is associated with a lower r-square in the factor model regressions by construction. In fact, this result holds for both alternative factor models and all four rebalancing horizons reported in Table 3.4.

[18]Note that the average adjusted r-squares reported in Table 3.4 are substantially lower than those mentioned at the end of Section 3.2.2 as the r-squares in Table 3.4 are average values based on the individual funds' r-squares while the r-squares in Section 3.2.2 are calculated at the index level.

Table 3.4: Alpha persistence of two-way sorted portfolios
This table reports the average monthly out-of-sample alphas of equally-weighted hedge fund portfolios sorted according to their 6-month (Panel A), 12-month (Panel B), 24-month (Panel C), and 36-month (Panel D) historical alpha and their 24-month SDI. The alpha sort is conducted for both alternative factor models: the SW alpha based on the stepwise regression approach and the FH alpha based on the Fung and Hsieh (2004) seven-factor model. Alphas are reported for different rebalancing frequencies, ranging from semi-annual (Panel A) to triennial (Panel D). The last column ('SDI only') reports the out-of-sample SW alpha for a pure SDI sort. The first and fifth columns ('alpha only') report the alpha from a pure historical alpha sort and the columns ('SDI high' and 'SDI low') the average alphas of the funds of the portfolios that are sorted according to their historical SW and FH alpha first and then according to their historical SDI, respectively. The columns ('Hi-Lo') report the difference in average alpha between the 'SDI high' and 'SDI low' columns. The table is based on all USD denominated funds with at least 24 non-backfilled observations (excluding funds of funds). The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004a). All alphas are expressed in monthly percentage returns, the corresponding t-values are reported in parentheses, and the average adjusted r-squares of each portfolio are reported in square brackets. The difference in means between the portfolios is tested using a standard t-test. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level.

Panel A: 6-month alpha persistence (semi-annual rebalancing)

	SW alpha				FH alpha				SW alpha
	alpha only	SDI high	SDI low	Hi - Lo	alpha only	SDI high	SDI low	Hi - Lo	SDI only
alpha 5	1.62 ***	1.88 ***	1.36 ***	0.51 ***	1.74 ***	1.89 ***	1.58 ***	0.31	0.37 ***
(highest)	(12.78)	(13.26)	(9.59)	(2.56)	(10.73)	(12.43)	(8.25)	(1.28)	(6.60)
	[0.29]	[0.15]	[0.43]		[0.25]	[0.13]	[0.37]		[0.17]
alpha 4	0.58 ***	0.67 ***	0.50 ***	0.17	0.64 ***	0.67 ***	0.61 ***	0.06	
	(6.65)	(7.23)	(5.27)	(1.32)	(7.04)	(7.96)	(5.55)	(0.46)	
	[0.30]	[0.15]	[0.45]		[0.27]	[0.14]	[0.40]		
alpha 3	0.18 ***	0.23 ***	0.14 *	0.09	0.25 ***	0.27 ***	0.23 ***	0.04	
	(3.03)	(4.23)	(1.86)	(0.95)	(3.62)	(3.91)	(3.05)	(0.36)	
	[0.32]	[0.17]	[0.46]		[0.28]	[0.14]	[0.41]		
alpha 2	-0.22 ***	-0.14 ***	-0.30 ***	0.15 *	-0.09	-0.08	-0.11	0.04	
	(-4.19)	(-3.09)	(-4.33)	(1.83)	(-1.41)	(-1.35)	(-1.37)	(0.37)	
	[0.35]	[0.20]	[0.49]		[0.29]	[0.16]	[0.42]		
alpha 1	-1.18 ***	-1.15 ***	-1.22 ***	0.07	-0.92 ***	-0.97 ***	-0.88 ***	-0.09	0.03
(lowest)	(-10.06)	(-9.64)	(-8.81)	(0.39)	(-7.34)	(-8.27)	(-5.46)	(-0.44)	(0.23)
	[0.33]	[0.20]	[0.47]		[0.29]	[0.17]	[0.41]		[0.46]
Hi - Lo	2.80 ***	3.03 ***	2.58 ***		2.66 ***	2.86 ***	2.46 ***		0.35 ***
	(16.21)	(6.50)	(13.02)		(12.97)	(14.89)	(9.83)		(2.82)

Table 3.4 — continued

Panel B: 12-month alpha persistence (annual rebalancing)

	SW alpha				FH alpha				SW alpha
	alpha only	SDI high	SDI low	Hi - Lo	alpha only	SDI high	SDI low	Hi - Lo	SDI only
alpha 5	1.39 ***	1.70 ***	1.07 ***	0.64 ***	1.57 ***	1.69 ***	1.45 ***	0.24	0.36 ***
(highest)	(12.78)	(8.70)	(7.08)	(2.58)	(9.00)	(7.31)	(9.53)	(0.86)	(5.74)
	[0.30]	[0.13]	[0.37]		[0.25]	[0.14]	[0.36]		[0.18]
alpha 4	0.50 ***	0.56 ***	0.44 ***	0.12	0.61 ***	0.65 ***	0.56 ***	0.09	
	(6.65)	(6.79)	(5.86)	(1.10)	(6.10)	(6.03)	(5.55)	(0.62)	
	[0.31]	[0.14]	[0.40]		[0.28]	[0.15]	[0.41]		
alpha 3	0.20 ***	0.24 ***	0.17 *	0.06	0.27 ***	0.26 ***	0.27 ***	-0.01	
	(3.03)	(3.65)	(1.92)	(0.57)	(3.33)	(2.89)	(3.58)	(-0.05)	
	[0.30]	[0.14]	[0.41]		[0.27]	[0.15]	[0.39]		
alpha 2	-0.20 ***	-0.16 **	-0.23 **	0.07	-0.05	-0.05	-0.05	0.00	
	(-4.19)	(-1.97)	(-2.09)	(0.54)	(-0.60)	(-0.56)	(-0.59)	(0.03)	
	[0.34]	[0.16]	[0.42]		[0.29]	[0.17]	[0.41]		
alpha 1	-0.90 ***	-0.89 ***	-0.92 ***	0.03	-0.74 ***	-0.79 ***	-0.70 ***	-0.09	0.04
(lowest)	(-10.06)	(-7.38)	(-5.15)	(0.12)	(-4.16)	(-4.53)	(-3.29)	(-0.32)	(0.31)
	[0.33]	[0.17]	[0.41]		[0.29]	[0.18]	[0.41]		[0.46]
Hi - Lo	2.29 ***	2.59 ***	1.98 ***		2.32 ***	2.48 ***	2.15 ***		0.32 **
	(16.26)	(11.28)	(8.50)		(9.27)	(8.56)	(8.22)		(2.23)

Panel C: 24-month alpha persistence (biennial rebalancing)

	SW alpha				FH alpha				SW alpha
	alpha only	SDI high	SDI low	Hi - Lo	alpha only	SDI high	SDI low	Hi - Lo	SDI only
alpha 5	1.08 ***	1.36 ***	0.81 ***	0.55 *	1.30 ***	1.51 ***	1.08 ***	0.44	0.30 ***
(highest)	(6.69)	(7.46)	(3.36)	(1.84)	(5.08)	(5.27)	(3.41)	(1.02)	(5.46)
	[0.33]	[0.22]	[0.44]		[0.28]	[0.19]	[0.38]		[0.19]
alpha 4	0.39 ***	0.45 ***	0.33 ***	0.12	0.53 ***	0.60 ***	0.47 ***	0.13	
	(5.22)	(7.00)	(3.16)	(1.01)	(4.44)	(4.68)	(3.78)	(0.73)	
	[0.29]	[0.17]	[0.41]		[0.28]	[0.18]	[0.38]		
alpha 3	0.19 ***	0.20 ***	0.18 *	0.01	0.21 ***	0.22 ***	0.20 **	0.02	
	(2.57)	(2.98)	(1.82)	(0.10)	(2.52)	(3.02)	(2.00)	(0.12)	
	[0.29]	[0.18]	[0.41]		[0.28]	[0.16]	[0.40]		
alpha 2	-0.10	-0.05	-0.14	0.09	0.01	0.01	0.02	-0.01	
	(-0.83)	(-0.53)	(-1.01)	(0.55)	(0.09)	(0.05)	(0.13)	(-0.05)	
	[0.32]	[0.20]	[0.44]		[0.27]	[0.16]	[0.38]		
alpha 1	-0.53 ***	-0.62 ***	-0.44 ***	-0.18	-0.51 ***	-0.65 ***	-0.36	-0.29	0.12
(lowest)	(-4.64)	(-4.14)	(-4.01)	(-0.98)	(-2.72)	(-3.63)	(-1.49)	(-0.95)	(0.81)
	[0.33]	[0.22]	[0.44]		[0.30]	[0.19]	[0.41]		[0.43]
Hi - Lo	1.61 ***	1.98 ***	1.24 ***		1.81 ***	2.17 ***	1.44 ***		0.18
	(8.15)	(8.40)	(4.71)		(5.70)	(6.39)	(3.61)		(1.17)

Table 3.4 — continued

Panel D: 36-month alpha persistence (triennial rebalancing)

	SW alpha				FH alpha				SW alpha
	alpha only	SDI high	SDI low	Hi - Lo	alpha only	SDI high	SDI low	Hi - Lo	SDI only
alpha 5	0.68 ***	0.61 **	0.76 ***	-0.15	0.83 ***	0.67 ***	0.99 ***	-0.33 ***	0.25 ***
(highest)	(3.31)	(2.04)	(3.91)	(-0.43)	(10.86)	(6.36)	(18.99)	(-2.77)	(4.37)
	[0.31]	[0.18]	[0.44]		[0.28]	[0.16]	[0.40]		[0.16]
alpha 4	0.28 ***	0.27	0.28 *	-0.01	0.44 ***	0.46 ***	0.42 ***	0.04	
	(4.73)	(1.29)	(1.94)	(-0.05)	(15.66)	(8.35)	(5.81)	(0.48)	
	[0.32]	[0.19]	[0.45]		[0.27]	[0.16]	[0.38]		
alpha 3	0.22 ***	0.37 ***	0.07	0.30 *	0.32 ***	0.36 **	0.27 ***	0.09	
	(5.16)	(2.43)	(0.64)	(1.65)	(5.00)	(2.31)	(4.00)	(0.53)	
	[0.30]	[0.17]	[0.43]		[0.27]	[0.15]	[0.39]		
alpha 2	0.00	0.10	-0.10 ***	0.21	0.07 *	0.12	0.02	0.11	
	(0.01)	(0.60)	(-2.81)	(1.19)	(1.82)	(1.55)	(0.25)	(0.96)	
	[0.32]	[0.20]	[0.43]		[0.28]	[0.17]	[0.40]		
alpha 1	-0.31 **	-0.31	-0.32 ***	0.01	-0.27 **	-0.34 *	-0.20 *	-0.14	0.10
(lowest)	(-2.09)	(-1.26)	(-5.46)	(0.04)	(-2.03)	(-1.71)	(-1.87)	(-0.64)	(1.15)
	[0.32]	[0.21]	[0.43]		[0.30]	[0.20]	[0.41]		[0.37]
Hi - Lo	0.99 ***	0.91 ***	1.08 ***		1.10 ***	1.01 ***	1.19 ***		0.15
	(3.90)	(2.37)	(5.32)		(7.19)	(4.49)	(10.15)		(1.47)

The results on the 12-month performance persistence in Panel B show a similar pattern. Again we find a monotonic increase of the portfolio alphas in the historical alpha. Moreover, the alpha of the high-SDI portfolio is always higher than the alpha of the corresponding low-SDI portfolio. Again, the differences between the high-alpha and low-alpha portfolios are all significant at the 1% level while the differences between the high- and low-SDI portfolios are insignificant with one exception (the alpha 5 sub-portfolio based on the SW alpha). As compared to the results on the 6-month performance persistence in Panel A, the differences in alphas between high- and low-alpha as well as between high- and low-SDI portfolios are reduced only slightly. When using one-way sorts based on either historical alpha or the SDI only, we still find significantly higher returns for the portfolio including hedge funds with high SDI as compared to the portfolio including low-SDI funds and for the high-alpha as compared to the low-alpha portfolios. The differences are significant at the 5% and 1% level, respectively. Most importantly, we find a two-way sort based on both alpha and SDI to further increase performance persistence and even more so than over the 6-month horizon. Specifically, the difference in alpha increases from 2.29% (2.32%) between the two extreme portfolios, when sorting is based on the SW alpha (FH alpha) only, to 2.62% (2.39%) when sorting is based on both SW alpha (FH alpha) and the SDI. This is an increase in alpha of 0.33% (0.07%) per month or 3.96% (0.84%) p.a.

The results on 24-month performance persistence are reported in Panel C and show that we find performance persistence even over a two-year period. We still find portfolio alphas to increase monotonically in both the historical alpha and the SDI with few exceptions (the FH alpha of the low-SDI sub-portfolios are larger than the FH alpha of the high-SDI sub-portfolios within the alpha 1 and alpha 2 portfolios and the SW alpha of the low-SDI sub-portfolio is larger than the SW alpha of the high-SDI sub-portfolio within the alpha 1 portfolio). The results from a one-way sort based on whether the SDI is above or below the median shows that the alpha of the high-SDI portfolio is larger and significant at the 1% level as compared to the insignificant alpha of the low-SDI portfolio. The difference between the alpha of the high- and the alpha of the low-SDI portfolios, however, is insignificant. In contrast, the differences in alpha between the high- and low-alpha portfolios amount to a monthly 1.61% (SW alpha) and 1.81% (FH alpha) and are significant at the 1% level. The alpha differences between the high-alpha/high-SDI portfolios and the low-alpha/low-SDI portfolios are 1.80% and 1.88% for the SW and FH alpha, respectively. Hence, the valued-added by additionally using the SDI as a second sorting criterion amounts to 0.19% (0.07%) monthly or 2.28% (0.84%) yearly for the SW (FH) alpha sorts.

The results on 36-month performance persistence in Panel D show that there is even economically and statistically significant performance persistence over a three-year period. Portfolio alphas increase almost monotonically in the historical alpha and the return difference between the high-alpha and low-alpha portfolios amount to 0.99% and 1.10% for the SW and FH alpha, respectively. However, SDI does no longer positively contribute to portfolio returns. The differences in portfolio returns between the high-SDI and low-SDI portfolios are often very small and sometimes even negative. In fact, the alpha differences between the high-alpha/high-SDI portfolios and the low-alpha/low-SDI portfolios of 0.92% (SW alpha) and 0.86% (FH alpha) are smaller than alpha differences resulting from one-way alpha sorted portfolios. Hence, additionally using the SDI as a second sorting criterion does not improve but deteriorate performance persistence.

We perform a number of robustness checks on these results. First, we reverse the order of the sorting procedure and start by sorting the hedge funds into two portfolios based on whether their SDI over the previous 24 months is above or below the median SDI. Then, we build five sub-portfolios within each of these two portfolios based on the historical 12-month SW alpha. The results for the 12-month horizon are reported in the first three columns of Table 3.5. Most importantly, the results show that the portfolio alphas still monotonically increase in both the historical alpha and the SDI. Moreover, the differences in SW alpha between the portfolios with the highest historical alpha (alpha 5) and the portfolios with the lowest historical alpha (alpha 1) of 2.44% and 2.05% remain significant at the 1% level. In addition, the differences in alphas between the high- and low-SDI portfolios somewhat increases in magnitude (and significance for the alpha 3 and alpha 4 portfolios). The alpha differences between the high-alpha/high-SDI portfolios and the low-alpha/low-SDI portfolios is 2.69% per month. Hence, the value added from using the two-way sort is even larger here as compared to Panel B of Table 4. As a second robustness test, we first sort the hedge funds into three SDI portfolios according to the SDI tercile and then into five portfolios according to the historical FH alpha. The results are reported in the fourth to seventh column and show a monotonic increase of portfolio alphas in the historical alpha as well as in SDI (with the exception of the alpha 1 sub-portfolio). The differences between the portfolios with the highest historical alpha and the portfolios with the lowest historical alpha of 2.36%, 1.52%, and 2.10% are all significant at the 1% level. In contrast, the differences between the high-SDI and low-SDI portfolios are all insignificant. The alpha differences between the high-alpha/high-SDI portfolios and the low-alpha/low-SDI portfolios is 2.50% per month. Hence, the benefit from using the SDI as a second sorting criterion is somewhat reduced as compared to the previous specifications. As a third robustness test, we first sort the hedge funds into decile portfolios based on historical alpha and then into two SDI-portfolios based on whether the SDI is above or below the median of the sub-portfolio. Again we find portfolio alphas to increase monotonically in both historical alphas and SDI. As in Tables 3.4 and 3.5, the difference in portfolio alpha resulting from additionally sorting based on the SDI is strongest for the highest-alpha decile. The results based on these alpha-decile portfolios are not reported for space reasons.[19] As a fourth robustness test, we repeat the analyses in Table 3.4 but use the t-values of the alpha instead of the alpha as the second sorting criterion.

Wang and Zheng (2008) propose two alternative hypotheses related to the relation between SDI and alpha. The first is the "skill hypothesis" which claims that managers with a high SDI have great new ideas and superior investment skills resulting in unique, proprietary trading strategies, while less skilled managers are more likely to herd. This hypothesis suggests a positive relation between SDI and fund performance. The "gaming hypothesis" states that funds may appear to deviate from their peers due to a potential conflict of interests between fund managers and investors, triggered by high-watermarks and other option-like characteristics of their compensation packages. These compensation packages might provide incentives for managers to take idiosyncratic risk in order to increase the chance of having extreme performance. Our results so far provide support for the skill hypothesis as we find a positive relation between SDI and alpha and between SDI and positive performance persistence. To further investigate the gaming hypothesis, we investigate the annual attrition rates of the portfolios reported in the first two columns of Table 3.5 as well as the attrition rates of portfolios that are either exclusively sorted based on the historical 12-month SW alpha or the SDI. The results are reported in the last four columns of Table 3.5. The attrition rate decreases monotonically in the historical SW alpha and increases in SDI. Hence, the portfolio with the highest historical alpha and an SDI below the median exhibits the lowest attrition rate of 7.1% while the portfolio with the lowest historical alpha and an above-median SDI exhibits the highest attrition rate of 20.0%—an increase by a factor of roughly 2.8. The finding of a higher attrition rate for funds with a high SDI is consistent with the results in Wang and Zheng (2008) as well as with the gaming hypothesis.

Although our sample includes both live and dead funds, there is no return data available after funds stop reporting. If some of the funds dropping out of the sample continue to operate and the (unreported) performance is substantially different from the performance of funds that do report, the portfolio returns which are only based on reporting funds would be biased. As the majority of funds that stop reporting to TASS do so because of a liquidation of the fund (e.g., Getmansky et al., 2004b) and delisting returns have been estimated to be significantly

[19] We performed all these robustness tests also for the 6-month, 24-month, and 36-month horizon and found the results to remain robust as well.

lower than reported returns (Hodder et al., 2009), a higher attrition rate is likely to indicate an upward bias in returns as the lower delisting returns are not available. To investigate whether the differences in portfolio returns in our sample can be (partly) explained by differences in delisting returns of funds dropping out of our sample, we would need return data for funds after dropping out of our sample which is naturally not available. Hence, we perform the same back-of-envelope calculations as in Wang and Zheng (2008) to investigate how low the alpha of defunct funds can be in the first year after dropping out of our sample in order to eliminate the alpha difference between the low and the high SDI portfolios. For the two portfolios constructed exclusively based on the funds' SDI (i.e., whether the SDI is above or below the median) the attrition rates are 13.2% (high SDI portfolio) and 10.6% (low SDI portfolio), respectively. This translates into an average annualized alpha of the disappearing fund that can be as low as -126.3% to make the return differences between the two portfolios to disappear.[20,21] In addition, the decrease in the attrition rate with increasing historical alphas does even enhance the alpha persistence we find in our sample. For example, for the two-way sorted portfolios in Panel B of Table 3.4, the attrition rate for the high-SDI and high-alpha portfolio is 10.1% and for the low-SDI and low-alpha portfolio 15.1%, respectively. Hence, accounting for the delisting returns of the hedge funds disappearing from the sample would presumably even increase the return differences between the two portfolios.

To account for the possible effect of outliers on our portfolio returns, we alternatively report portfolio median returns. The results in Panel A of Table 3.6 show that for a 12-month horizon our results still hold based on medians while the median returns of the extreme portfolios (i.e., the alpha 1 and alpha 5 portfolios) are somewhat reduced in absolute terms, i.e. less negative for the alpha 1 portfolio and less positive for the alpha 5 portfolio. Alpha persistence amounts to a sizable 1.84% (1.90%) per month for the SW (FH) alpha and the alpha contribution from additionally sorting for SDI is 0.43% (0.08%) per month (or 5.16% (0.96%) p.a.). Over the 24-month horizon, alpha persistence is reduced to 1.15% (1.40%) for the SW (FH) alpha and the contribution of the SDI sort to 0.04% (0.01%) per month. For the 36-month time horizon, alpha persistence is reduced to 0.85% (0.92%) per month for the SW (FH) alpha while the effect

[20] Wang and Zheng (2008) perform their back-of-envelope calculations for five portfolios sorted based on the funds' SDI only. If we repeat their analysis, we find annual attrition rates of 13.7% for the highest-SDI portfolio and 9.9% for the lowest-SDI portfolio. The corresponding monthly alphas are 0.59% and 0.09%, respectively. This translates in an average annual alpha of below -147.6% for the defunct funds to eliminate the difference in alphas between the two portfolios. For comparison, Wang and Zheng (2008) report a value -101.8%.

[21] In their recent study, Hodder et al. (2009) use estimated portfolio holdings for funds of hedge funds with reported returns to back out maximum likelihood estimates for hedge funds' delisting returns. Across all delisting hedge funds, they estimate a mean delisting return of -1.86% which compares with a mean monthly return for all hedge funds in their sample of 1.01%.

Table 3.5: Alpha persistence of two-way sorted portfolios and attrition rates

The table reports the average monthly out-of-sample alpha of annually-rebalanced equally-weighted hedge funds portfolios. The portfolios in the first two columns are first sorted according to their 24-month SDI and second according to their historical 12-month SW alpha from a stepwise regression approach. The third column ('Hi-Lo') reports the difference in average alpha between the 'SDI high' and 'SDI low' columns. The next three columns report the average alpha based on the Fung and Hsieh (2004) seven-factor model of portfolios that are first sorted into three SDI categories and then into five portfolios according to their historical FH alpha. The seventh column ('Hi-Lo') again reports the difference in average alpha between the 'SDI high' and 'SDI low' columns. The last four columns report the annual average attrition rate of the portfolios reported in the first two columns and the attrition rate of portfolios that are only sorted according to their historical alpha and their historical SDI. The table is based on all USD denominated funds with at least 24 non-backfilled observations (excluding funds of funds). The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004a). All alphas are expressed in monthly percentage returns and the corresponding t-values are reported in parentheses. The difference in means between the portfolios is tested using a standard t-test. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level.

	SW alpha			FH alpha				Attrition rate		Attrition rate	
	SDI high	SDI low	Hi - Lo	SDI high	SDI med	SDI low	Hi - Lo	SDI high	SDI low	alpha only	SDI only
alpha 5	1.68 ***	1.04 ***	0.65 ***	1.75 ***	1.50 ***	1.35 ***	0.39	0.101	0.071	0.090	0.137
(highest)	(9.40)	(5.80)	(2.57)	(10.47)	(6.91)	(5.27)	(1.29)				
alpha 4	0.60 ***	0.38 ***	0.22 *	0.72 ***	0.58 ***	0.50 ***	0.22	0.106	0.081	0.092	0.132
	(9.22)	(3.95)	(1.84)	(9.67)	(5.85)	(3.12)	(1.27)				
alpha 3	0.31 ***	0.04	0.26 **	0.28 ***	0.27 ***	0.26 *	0.02	0.111	0.101	0.111	0.118
	(5.29)	(0.43)	(2.21)	(4.70)	(3.72)	(1.84)	(0.14)				
alpha 2	-0.05	-0.27 *	0.22	0.03	-0.02	-0.11	0.15	0.143	0.126	0.128	0.109
	(-0.70)	(-1.89)	(1.36)	(0.66)	(-0.31)	(-0.82)	(0.99)				
alpha 1	-0.76 ***	-1.01 ***	0.26	-0.61 ***	-0.02 ***	-0.75 ***	0.14	0.200	0.151	0.176	0.099
(lowest)	(-7.50)	(-5.23)	(1.18)	(-5.73)	(-3.90)	(-2.58)	(0.44)				
Hi - Lo	2.44 ***	2.05 ***		2.36 ***	1.52 ***	2.10 ***					
	(11.87)	(7.78)		(11.91)	(7.02)	(6.35)					

of additionally sorting for SDI disappears altogether. The results on the 24- and 36-month horizons are not reported for space reasons.

Kosowski et al. (2006) and Kosowski et al. (2007) argue that ranking funds by the t-statistic of their alpha instead of alpha controls for differences in risk-taking across funds. Moreover, they present a number of statistical arguments to justify that the t-statistic of alpha is preferable to alpha. Hence, as a further robustness check, we sort our portfolios based on the t-statistics of the alpha and SDI. The results on the 12-month horizon in Panel B show that using the t-statistic of alpha instead of alpha again does not qualitatively change the results. Alpha significance is somewhat lower as compared to Panel A and amounts to 1.59% (1.60%) for the SW (FH) alpha. and the alpha contribution from additionally sorting for SDI is 0.09% (0.01%) per month (or 1.08% (0.12%) p.a.). As in Panel A, alpha persistence and the contribution of additionally sorting for SDI decreases for longer time horizons and the latter disappears altogether over a 36-month horizon. The results on the 24- and 36-month horizons are not reported for space reasons.

In Table 3.7, we investigate the performance persistence resulting from a sorting based on raw returns as well as the persistence in raw returns. We start by using raw returns instead of alphas as a first sorting criterion (and again the SDI as a second sorting criterion) to build portfolios and then calculate the average monthly alphas of these portfolios. The first six columns in Panels A, B, C, and D report the results on 6-month, 12-month, 24-month, and 36-month persistence based on the SW and the FH alpha, respectively. As in Tables 3.4 and 3.5, the results show that portfolio alphas increase monotonically in both the historical returns and the SDI for horizons up to 24 months with two exceptions (over a 24-month horizon, both the SW and the FH alphas are higher for the low-SDI than the high-SDI portfolios in the lowest return sub-portfolios). The differences in alpha between the high-return (return 5) and the low-return portfolios (return 1) are all significant at the 1% level. Over a 36-month horizon, alphas still increase almost monotonically in historical returns and the differences in alpha between the high-return (return 5) and the low-return portfolios (return 1) are all significant at the 5% level or better. However, there is no clear pattern in alphas between high- and low-SDI portfolios anymore. In contrast to Tables 3.4 and 3.5, the difference between the high-SDI and low-SDI portfolios are all significant at the 10% level or better for the 6- and 12-month horizons and the SW alpha but mostly insignificant otherwise. In the seventh to ninth columns of Table 3.7, we investgiate the persistence in raw returns and report the portfolios' annual effective cumulative raw returns. In Panel A, we find the portfolio raw returns to increase monotonically in both the historical returns and the SDI. The differences in annual returns between high-return (return 5)

Table 3.6: Alpha persistence of two-way sorted portfolios based on medians and t-statistics
Panel A of the table reports the median monthly out-of-sample alphas of hedge funds in portfolios sorted according to their 12-month historical alpha and their 24-month SDI. The alpha sort is conducted for both alternative factor models: the SW alpha based on the stepwise regression approach and the FH alpha based on the Fung and Hsieh (2004) seven-factor model. The last column ('SDI only') reports the median out-of-sample SW alpha for a pure SDI sort. The first and fifth columns ('alpha only') report the median alpha from a pure historical alpha sort and the columns ('SDI high' and 'SDI low') the median alphas of the funds in portfolios that are first sorted according to their historical SW and FH alphas and then according to their historical SDI, respectively. The columns ('Hi-Lo') report the difference in average alpha between the 'SDI high' and 'SDI low' columns. Panel B replicates the structure of Panel A but reports the mean alpha of equally-weighted portfolios where the sort is based on the historical t-statistics of the SW and FH alpha instead of the alphas. The table is based on all USD denominated funds with at least 24 non-backfilled observations (excluding funds of funds). The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004a). All alphas are expressed in monthly percentage returns and the corresponding t-values are reported in parentheses. The difference in medians between the portfolios is tested using a standard t-test. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level.

Panel A: 12-month alpha persistence (annual rebalancing): portfolio medians

	SW alpha				FH alpha				SW alpha
	alpha only	SDI high	SDI low	Hi - Lo	alpha only	SDI high	SDI low	Hi - Lo	SDI only
alpha 5	1.14 ***	1.38 ***	0.96 ***	0.41 **	1.33 ***	1.38 ***	1.30 ***	0.08	0.30 ***
(highest)	(9.64)	(7.95)	(8.21)	(1.97)	(10.33)	(9.10)	(10.35)	(0.41)	(5.97)
alpha 4	0.53 ***	0.60 ***	0.46 ***	0.13	0.60 ***	0.64 ***	0.58 ***	0.07	
	(7.20)	(6.05)	(6.13)	(1.07)	(7.00)	(6.68)	(6.82)	(0.52)	
alpha 3	0.22 ***	0.23 ***	0.18 ***	0.05	0.27 ***	0.30 ***	0.26 ***	0.04	
	(3.86)	(4.29)	(2.46)	(0.51)	(3.74)	(3.98)	(3.62)	(0.38)	
alpha 2	-0.15 **	-0.12 **	-0.16	0.05	-0.05	-0.06	-0.04	-0.03	
	(-2.03)	(-2.15)	(-1.62)	(0.40)	(-0.62)	(-0.71)	(-0.40)	(-0.21)	
alpha 1	-0.70 ***	-0.60 ***	-0.90 ***	0.30	-0.57 ***	-0.54 ***	-0.60 ***	0.06	0.06
(lowest)	(-6.03)	(-7.21)	(-5.38)	(1.62)	(-3.75)	(-3.64)	(-3.69)	(0.27)	(0.55)
Hi - Lo	1.84 ***	1.97 ***	1.86 ***		1.90 ***	1.92 ***	1.90 ***		0.24 **
	(11.09)	(10.28)	(9.12)		(9.54)	(9.06)	(9.26)		(2.00)

Table 3.6 — continued

Panel B: 12-month alpha persistence (annual rebalancing): sorted for alpha t-stats

	SW alpha							FH alpha						
	t-stat only		SDI high		SDI low		Hi - Lo	t-stat only		SDI high		SDI low		Hi - Lo
t-stat 5	0.90	***	1.04	***	0.77	***	0.27	1.06	***	1.10	***	1.01	***	0.09
(highest)	(8.15)		(9.37)		(5.45)		(1.49)	(7.74)		(7.34)		(7.54)		(0.44)
t-stat 4	0.73	***	0.86	***	0.59	***	0.26	0.74	***	0.76	***	0.72	***	0.05
	(7.27)		(6.33)		(5.40)		(1.51)	(6.30)		(9.26)		(4.40)		(0.27)
t-stat 3	0.23	***	0.32	***	0.14		0.18	0.42	***	0.47	***	0.37	***	0.10
	(2.55)		(3.68)		(1.01)		(1.09)	(4.22)		(3.81)		(2.85)		(0.54)
t-stat 2	-0.18		-0.05		-0.31	*	0.26	-0.01		0.01		-0.04		0.04
	(-1.35)		(-0.41)		(-1.76)		(1.22)	(-0.11)		(0.05)		(-0.23)		(0.21)
t-stat 1	-0.69	***	-0.74	***	-0.64	***	-0.10	-0.54	***	-0.58	***	-0.51	***	-0.07
(lowest)	(-6.89)		(-6.61)		(-6.14)		(-0.67)	(-4.01)		(-3.97)		(-3.04)		(-0.32)
Hi - Lo	1.59	***	1.78	***	1.41	***		1.60	***	1.68	***	1.52	***	
	(10.67)		(11.29)		(8.03)			(8.31)		(8.03)		(7.09)		

and low-return portfolios (return 1) amount to 11.09% and 9.41% and are significant at the 1% and 10% level for the high- and the low-SDI portfolios, respectively. In contrast, the differences between the high- and low-SDI portfolios are all insignificant. Over the 12-month and 24-month time horizons, we still find evidence of persistence in raw returns in the high-return portfolios. However, the differences in annual returns between the high-return (return 5) and the low-return portfolios (return 1) are all insignificant. Moreover, the relation between SDI and portfolio returns becomes ambiguous. Over the 36-month horizon (Panel D), we find no evidence of performance persistence in raw returns. The last two columns of Table 3.7 report the returns of one-way sorted portfolios based on their historical returns and their SDI, respectively. For time horizons of up to 24 months, we find a positive return contribution from using a two-way sort based on both historical returns and the SDI as compared to using one-way sorts based on historical returns only. The differences in portfolio returns between the high-return / high-SDI portfolio and the low-return / low-SDI portfolio are 11.12%, 5.26%, and 6.94% p.a. for the 6-month, 12-month, and 24-month time horizons, respectively. The corresponding values from the one-way sorted portfolios based on historical returns are 10.25%, 4.06%, and 5.17%, respectively.

We alternatively also tested two-way portfolio sorts based on alphas and other variables than the SDI. As SDI turned out to be the variable with the highest explanatory power for alpha persistence (Table 3.2) as well as alphas (Table 3.3), we started by using the SDI as the second sorting criterion besides historical alpha. We repeated the complete set of analyses and used relative fund flows, fund size, as well as the measures of illiquidity as second sorting criterion besides historical alpha. While the effect resulting from using the SDI as a second sorting criterion turned out to be substantial and economically meaningful, the effect resulting from using these alternative fund characteristics as second sorting criterion is relatively small and not robust. In fact, we found none of these fund characteristics to systematically help in improving the alpha (or return) persistence. Hence the results from these alternative two-way sorts are not reported in a table for space reasons.

We also repeated our main analyses on the strategy level and found alpha persistence and a positive contribution to portfolio alphas resulting from an additional sorting based on the SDI for all nine tested strategies.[22] Over a 12-month horizon, alpha persistence is highest for the strategies Emerging Markets, Equity Market Neutral, Event Driven, and Managed Futures. The difference in portfolio alphas based on SDI-sorting is highest for the strategy Managed Futures

[22]Due to the very small sample size, we excluded the strategy Dedicated Short Bias from this analysis.

and Emerging Markets. The difference in alpha between the high-alpha / high-SDI portfolio and the low-alpha / low-SDI portfolio is largest for the strategy Managed Futures. For space reasons, we do not report the results on the strategy level.[23]

One potential concern with our results may be that they are influenced by the desmoothing of returns as described in Section 3.2.1. In fact, the procedure suggested by Getmansky et al. (2004a) to desmooth the returns reported in hedge fund databases may increase persistence by picking up information contained in previous returns in the MA(2) estimations. Therefore, we repeat all analyses based on reported instead of desmoothed returns. We find the results to remain basically unchanged as compared to the results reported in Tables 3.4 to 3.7. Hence, for space reasons we do not report any of these results in a table.[24]

Finally, we investigate whether (and how) the recent credit crisis of 2008 affects our results. We do this based on three alternative approaches. In the first approach, we investigate whether our results hold during the crisis period based on TASS data from September 2007 to June 2009.[25] As in Table 4, we then sort all 1,164 hedge funds in this sample into five quintile-portfolios based on their historical performance over the 12-month period from September 2007 to August 2008. We then split each of these five portfolios into two sub-portfolios based on their SDI and calculate the performance of these 10 portfolios as well as the five alpha-sorted portfolios, and the two SDI-sorted portfolios over the 10-month period from September 2008 to June 2009. In September 2008, Lehman's filing for Chapter 11 bankruptcy protection ushered in an extended period of the worst deteriorations in stock returns during the financial crisis.

The results for both the SW and FH alphas are reported in Table 3.8. Most importantly, the results show that the alpha 5 portfolios always exhibit the highest alpha and the alpha 1 portfolios the lowest alphas. The differences in alphas between the alpha 5 and alpha 1 portfolios are all significant at the 1% level and indicate monthly return differences of between 1.35% and 1.73%. However, both the SW and the FH alphas show no ordering according to their historical performance across alpha portfolios 2 to 4. A comparison of the high-alpha/high-SDI portfolios' alphas with the alphas of the low-alpha/low-SDI portfolios shows that an additional sorting based on SDI does not further improve alpha persistence. In fact, the results from a pure SDI-sorting show that a higher SDI is associated with significantly lower returns during the crisis period. This finding is consistent with high-SDI funds taking on larger (idiosyncratic) risks that

[23]The full set of results, however, is available upon request.

[24]The results are available upon request.

[25]Unfortunately, we were unable to obtain CISDM data for the time period from January 2009 to June 2009.

Table 3.7: Alpha and return persistence of two-way sorted portfolios

The table reports the average monthly out-of-sample alpha based on the SW and FH models, as well as the annual return of equally-weighted hedge fund portfolios that are first sorted according to their 6-month (Panel A), 12-month (Panel B), 24-month (Panel C), and 36-month (Panel D) cumulative return and then according to their historical 24-month SDI. Portfolios are rebalanced from semi-annually to triennial (Panels A to D). The last two columns report the returns of one-way sorted portfolios based on their historical returns and their SDI. Alphas are expressed in monthly percentage returns and returns in annual cumulative returns. Panels A to C are based on all USD denominated funds with at least 24 non-backfilled observations (excluding funds of funds) and Panel D on funds with at least 36 non-backfilled observations. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004a). T-values are in parentheses. The difference in means between the portfolios is tested using a standard t-test. *, **, and *** indicates significance on the 90%, 95%, and 99% confidence level.

Panel A: 6-month return and alpha persistence (semi-annual rebalancing)

	SW alpha			FH alpha			Return				
	SDI high	SDI low	Hi - Lo	SDI high	SDI low	Hi - Lo	SDI high	SDI low	Hi - Lo	Return	SDI only
return 5	1.09 ***	0.64 ***	0.45 ***	1.10 ***	0.88 ***	0.22	16.50 ***	14.78 ***	1.72 *	15.64 ***	8.49 ***
(highest)	(10.56)	(5.15)	(2.78)	(12.46)	(6.81)	(1.42)	(7.56)	(6.76)	(0.56)	(7.61)	(6.12)
return 4	0.42 ***	0.21 ***	0.22 ***	0.44 ***	0.38 ***	0.06	11.07 ***	9.81 ***	1.26	10.44 ***	
	(8.21)	(2.82)	(2.41)	(11.75)	(4.87)	(0.68)	(6.87)	(6.34)	(0.56)	(6.94)	
return 3	0.23 ***	0.00	0.23 ***	0.25 ***	0.11 ***	0.13 ***	7.91 ***	7.36 ***	0.55	7.64 ***	
	(6.07)	(-0.01)	(3.81)	(7.89)	(2.40)	(2.40)	(6.28)	(3.78)	(0.24)	(4.88)	
return 2	0.06	-0.11	0.17 *	0.05	-0.01	0.06	6.54 ***	5.38 **	1.17	5.96 ***	
	(1.05)	(-1.61)	(1.90)	(0.92)	(-0.06)	(0.54)	(3.76)	(2.06)	(0.37)	(2.83)	
return 1	-0.38 ***	-0.63 ***	0.25 *	-0.36 ***	-0.43 ***	0.07	5.41 *	5.38	0.03	5.39	8.18 ***
(lowest)	(-4.37)	(-5.17)	(1.67)	(-3.90)	(-2.57)	(0.38)	(1.91)	(1.22)	(0.01)	(1.54)	(3.42)
Hi - Lo	1.47 ***	1.27 ***		1.46 ***	1.31 ***		11.09 ***	9.41 *		10.25 ***	0.31
	(10.90)	(7.30)		(11.47)	(6.20)		(3.11)	(1.91)		(2.52)	(0.11)

Panel B: 12-month return and alpha persistence (annual rebalancing)

	SW alpha			FH alpha			Return				
	SDI high	SDI low	Hi - Lo	SDI high	SDI low	Hi - Lo	SDI high	SDI low	Hi - Lo	Return	SDI only
return 5	1.13 ***	0.70 ***	0.43 **	1.22 ***	0.99 ***	0.23	14.31 ***	11.12 ***	3.19	12.72 ***	8.60 ***
(highest)	(8.41)	(4.18)	(2.02)	(8.95)	(5.20)	(0.99)	(4.21)	(3.19)	(0.66)	(3.86)	(5.05)
return 4	0.52 ***	0.21 *	0.31 **	0.51 ***	0.44 ***	0.07	9.95 ***	8.73 ***	1.22	9.34 ***	
	(6.50)	(1.85)	(2.24)	(8.07)	(4.42)	(0.61)	(5.06)	(4.88)	(0.46)	(5.23)	
return 3	0.28 ***	0.04	0.24 **	0.31 ***	0.20 *	0.11	7.80 ***	7.90 ***	-0.10	7.85 ***	
	(4.89)	(0.45)	(2.08)	(5.63)	(1.90)	(0.91)	(4.30)	(4.09)	(-0.04)	(4.34)	
return 2	0.06	-0.17 **	0.23 **	0.05	-0.03	0.08	6.55 ***	7.66 ***	-1.11	7.10 ***	
	(0.88)	(-1.99)	(2.10)	(0.88)	(-0.30)	(0.72)	(3.94)	(3.40)	(-0.39)	(3.72)	
return 1	-0.27 ***	-0.58 ***	0.31 *	-0.27 **	-0.46 **	0.19	8.26 ***	9.05 *	-0.79	8.66 **	9.31 ***
(lowest)	(-2.35)	(-3.87)	(1.66)	(-2.09)	(-2.26)	(0.80)	(2.92)	(1.90)	(-0.14)	(2.31)	(3.45)
Hi - Lo	1.40 ***	1.28 ***		1.49 ***	1.44 ***		6.05	2.07		4.06	-0.71
	(7.95)	(5.69)		(7.96)	(5.20)		(1.37)	(0.35)		(0.81)	(-0.22)

Table 3.7 — continued

Panel C: 24-month return and alpha persistence (biennial rebalancing)

	SW alpha			FH alpha			Return				
	SDI high	SDI low	Hi - Lo	SDI high	SDI low	Hi - Lo	SDI high	SDI low	Hi - Lo	Return	SDI only
return 5	0.93 ***	0.63 ***	0.29	1.03 ***	0.88 ***	0.15	14.60 ***	12.58 ***	2.02	13.61 ***	9.69 ***
(highest)	(6.82)	(2.66)	(1.07)	(4.98)	(2.94)	(0.42)	(4.50)	(3.31)	(0.40)	(4.12)	(11.27)
return 4	0.50 ***	0.21	0.28	0.57 ***	0.46 **	0.11	10.62 ***	11.90 ***	-1.27	11.26 ***	
	(5.25)	(1.32)	(1.53)	(10.03)	(2.25)	(0.51)	(7.52)	(4.81)	(-0.45)	(6.03)	
return 3	0.28 ***	0.01	0.27 *	0.34 ***	0.21	0.14	9.25 ***	9.46 ***	-0.21	9.35 ***	
	(3.61)	(0.05)	(1.75)	(4.16)	(1.03)	(0.63)	(10.88)	(5.27)	(-0.10)	(7.64)	
return 2	0.20	-0.10	0.30	0.22	-0.01	0.23	7.99 ***	8.54 ***	-0.56	8.27 ***	
	(1.38)	(-0.63)	(1.41)	(1.40)	(-0.06)	(0.93)	(4.66)	(4.02)	(-0.20)	(4.43)	
return 1	-0.35 ***	-0.22 **	-0.14	-0.39 ***	-0.19	-0.20	9.21 ***	7.67 ***	1.54	8.44 ***	10.73 ***
(lowest)	(-3.42)	(-2.43)	(-1.00)	(-2.88)	(-0.89)	(-0.79)	(5.22)	(7.03)	(0.74)	(6.97)	(4.51)
Hi - Lo	1.28 ***	0.85 ***		1.43 ***	1.07 ***		5.39	4.91		5.17	-1.04
	(7.49)	(3.34)		(5.75)	(2.90)		(1.46)	(1.24)		(1.47)	(-0.41)

Panel D: 36-month return and alpha persistence (triennial rebalancing)

	SW alpha			FH alpha			Return				
	SDI high	SDI low	Hi - Lo	SDI high	SDI low	Hi - Lo	SDI high	SDI low	Hi - Lo	Return	SDI only
return 5	0.45 ***	0.47 ***	-0.02	0.62 ***	0.85 ***	-0.23	8.95 ***	7.57 **	1.38	8.27 ***	8.85 ***
(highest)	(2.93)	(2.47)	(-0.09)	(3.12)	(9.62)	(-1.05)	(2.90)	(2.02)	(0.28)	(2.43)	(4.43)
return 4	0.46 ***	0.13	0.33 **	0.43 ***	0.41 ***	0.03	9.10 ***	8.60 ***	0.50	8.85 ***	
	(3.30)	(1.42)	(1.98)	(7.88)	(8.81)	(0.35)	(3.04)	(4.13)	(0.14)	(3.65)	
return 3	0.27 **	0.06	0.21	0.27 ***	0.23 ***	0.04	9.02 ***	7.58 ***	1.44	8.31 ***	
	(2.16)	(1.07)	(1.56)	(12.20)	(8.05)	(0.99)	(3.78)	(4.79)	(0.50)	(4.29)	
return 2	0.13	-0.01	0.14	0.14	0.09 *	0.06	7.34 ***	8.77 ***	-1.43	8.05 ***	
	(1.17)	(-0.41)	(1.23)	(1.60)	(1.70)	(0.56)	(8.69)	(4.40)	(-0.66)	(6.12)	
return 1	0.00	-0.22	0.22	-0.10	-0.16	0.07	10.86 ***	9.83 ***	1.03	10.35 ***	8.57 ***
(lowest)	(-0.02)	(-1.62)	(1.10)	(-0.69)	(-1.36)	(0.36)	(3.80)	(2.39)	(0.21)	(3.03)	(3.30)
Hi - Lo	0.45 **	0.69 ***		0.71 ***	1.01 ***		-1.91	-2.26		-2.08	0.28
	(2.16)	(2.95)		(2.95)	(6.84)		(-0.45)	(-0.40)		(-0.43)	(0.08)

Table 3.8: Alpha persistence of two-way sorted portfolios during the financial crisis
The table reports the average monthly out-of-sample alphas of hedge funds in portfolios sorted according to their 12-month historical alpha, calculated over the time period from September 2007 to August 2008, as well as their 24-month SDI. The out-of-sample portfolio performance is then evaluated over the 10-month crisis period from September 2008 to June 2009. The alpha sort is conducted for both alternative factor models: the SW alpha based on the stepwise regression approach and the FH alpha based on the Fung and Hsieh (2004) seven-factor model. The last column ('SDI only') reports the median out-of-sample SW alpha for a pure SDI sort. The first and fifth columns ('alpha only') report the median alpha from a pure historical alpha sort and the columns ('SDI high' and 'SDI low') the median alphas of the funds in portfolios that are first sorted according to their historical SW and FH alphas and then according to their historical SDI, respectively. The columns ('Hi-Lo') report the difference in average alpha between the 'SDI high' and 'SDI low' columns. The table is based on all USD denominated funds included in the TASS database with at least 24 non-backfilled observations (excluding funds of funds). The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004a). All alphas are expressed in monthly percentage returns and the corresponding t-values are reported in parentheses. The difference in medians between the portfolios is tested using a standard t-test. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level.

	SW alpha				FH alpha				SW alpha
	alpha only	SDI high	SDI low	Hi - Lo	alpha only	SDI high	SDI low	Hi - Lo	SDI only
alpha 5	0.95 ***	0.69 ***	1.22 ***	-0.53 **	1.05 ***	0.97 ***	1.13 ***	-0.16	-0.18
(highest)	(7.68)	(3.76)	(7.42)	(-2.15)	(7.23)	(4.04)	(10.38)	(-0.60)	(-1.14)
alpha 4	-0.15	-0.14 *	-0.15	0.01	0.01	-0.23	0.24 ***	-0.47	
	(-1.55)	(-1.79)	(-0.37)	(0.03)	(0.03)	(-0.58)	(4.60)	(-1.18)	
alpha 3	0.11	0.13	0.09	0.04	0.03	0.06	0.00	0.06	
	(1.35)	(1.13)	(1.06)	(0.25)	(0.19)	(0.43)	(-0.02)	(0.36)	
alpha 2	-0.24 *	-0.37 ***	-0.12	-0.25	-0.05	0.01	-0.11	0.13	
	(-1.69)	(-2.44)	(-0.98)	(-1.29)	(-0.51)	(0.10)	(-0.73)	(0.64)	
alpha 1	-0.74 ***	-0.97 ***	-0.51	-0.46	-0.35 *	-0.46 ***	-0.23	-0.24	0.15 *
(lowest)	(-4.07)	(-3.91)	(-0.95)	(-0.78)	(-1.82)	(-3.10)	(-0.67)	(-0.65)	(1.96)
Hi - Lo	1.69 ***	1.66 ***	1.73 ***	1.20 **	1.39 ***	1.43 ***	1.35 ***	1.19 ***	-0.33 *
	(7.69)	(5.38)	(3.08)	(2.11)	(5.83)	(5.07)	(3.81)	(2.88)	(-1.90)

are likely to show in lower returns during the crisis period. In the second approach, we reestimate Table 3.4 and drop all observations in year 2008 to remove any potential effect of the crisis on our results. The results remain virtually unchanged as compared to Table 3.4 and therefore are not reported in a table. Third, we reestimate Table 3.4 for an augmented dataset including the TASS data from January 2009 to June 2009 to better account for the effect of the crisis on our results. Again we find the results to remain virtually unchanged and, to save space, do not report them in a table.[26]

3.4 Conclusion

This chapter investigates the performance persistence of hedge funds from 1994 to 2008 based on a merged sample from the Lipper/TASS and the CISDM databases. We focus on long-term performance persistence and investigate time horizons of between 6 and 36 months because in light of notice and redemption periods the knowledge of short-term performance persistence does not add a great deal of value for investors. We estimate alpha by benchmarking hedge fund returns against two alternative 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). The dynamics in factor exposures are accounted for by using a rolling-window regression approach.

We find alpha persistence of up to three years which is both economically and statistically highly significant. Persistence in raw returns is economically substantial for time horizons up to two years as well but statistically significant only over a six-month horizon. We then attempt to improve the performance persistence by identifying fund characteristics that are related to the probability of exhibiting performance persistence. We estimate panel probit regressions of an indicator variable for whether a fund exhibits performance persistence on a number of fund characteristics. The fund characteristics we include in this analysis are fund size, fund age, relative fund flows, a dummy variable whether the fund is closed to new investments, the length of the notice and the length of the redemption period, management and incentive fees, leverage, a dummy variable for whether the fund management is personally invested in the fund, and a 'Strategy Distinctiveness Index' (SDI) as originally suggested by Wang and Zheng (2008). This SDI attempts to measure manager skills and the uniqueness of the hedge funds' trading strategies. The results from the probit analysis show that all these fund characteristics

[26]The results from the second and third approach are available upon request.

are significantly related to the probability of observing performance persistence. However, by using two-way sorts and forming hedge fund portfolios not only based on the funds' historical alpha but also on one of these fund characteristics, we find only the SDI to have the ability to systematically improve performance persistence over time horizons up to two years. Our results are robust with respect to the factor model we use for measuring hedge fund alpha, the benchmark we use for calculating the SDI, the quantiles used to form portfolios (i.e., median, tercile, quartile, and quintile), and whether the analysis is based reported or desmoothed returns. Only during the credit crisis of 2008, the positive contribution of the SDI disappears indicating that high-SDI funds may take on larger idiosyncratic risks that show up in lower returns during crisis periods.

Chapter 4

Benchmarking Hedge Funds: The Choice of the Factor Model

4.1 Introduction

Hedge funds have become widely used investment vehicles. The assets under management by hedge funds are estimated to have increased from roughly USD 50bn in January 1994 to USD 1,090bn in June 2009, with a peak of 1,546bn in June 2007, corresponding to an average annual increase of 22%.[1] Nevertheless, the discussion of and search for adequate specifications of risk-factor models to assess hedge fund performance, or alphas, is still ongoing. The most widely used (and accepted) factor model is the seven-factor model proposed by Fung and Hsieh (2004), henceforth referred to as "FH model". Examples of recent studies using this model include: Kosowski et al. (2007), Naik et al. (2007), Fung et al. (2008), Titman and Tiu (2008), and Sun et al. (2009).

Besides two equity-oriented risk factors (the S&P 500 index return and a size spread factor) and two bond-oriented risk factors (the monthly change in the 10-year treasury constant maturity yield and the monthly change in the credit spread), the FH model includes three trend-following risk factors on bonds, currencies, and commodities. These trend-following factors, labeled "primitive trend following strategies" (PTFS) are based on Fung and Hsieh (2001) and constructed as portfolios of lookback straddles calculated from exchange traded options.[2] Fung and Hsieh (2001) argue that hedge funds acting as trend followers are betting on big price moves. Hence,

[1] These estimates exclude funds of hedge funds and are based on the TASS Asset Flow Report of Q4, 2009.

[2] A lookback straddle consists of a lookback call and lookback put option on the same underlying and with the same strike price. A lookback call (put) option is an option that gives the holder the right to buy (sell) the underlying asset at its minimum (maximum) price during the lookback period.

similar to option buyers, they earn money in volatile markets. In fact, Fung and Hsieh (2001) show that these PTFS factors are highly correlated with the returns of trend following hedge funds (i.e., Managed Futures or CTAs) and show a high explanatory power in factor model regressions of such hedge fund returns.[3]

Recently, David Hsieh, on his data library website, suggested to add an eighth risk-factor to the FH model, the MSCI emerging markets index return. To the best of our knowledge, this extended factor model has not yet been used in academic studies. Moreover, recent papers have increasingly started to use statistical procedures to specify factor models, mostly a forward stepwise regression approach (e.g., Agarwal and Naik, 2004; Titman and Tiu, 2008; Zhong, 2008; Ammann et al., 2010a, 2010b). These papers show that, as expected, the explanatory power of such factor models that select the risk factors based on stepwise regressions increases as compared to the FH model while alpha decreases. The results, however, do not differ substantially and can be considered to be "qualitatively identical", i.e., there is rarely a change in the sign or the significance level of the alpha estimate.

In this chapter, we compare three different factor models, the FH seven-factor model, the extended FH eight-factor model (FH8 model), and a model based on a forward stepwise regression approach (SW model). First, we confirm the findings in previous studies (e.g., Titman and Tiu, 2008; Ammann et al., 2010a, 2010b) that over a longer time horizon from January 1994 to June 2009 there are little differences in the alphas resulting from the three alternative factor models although the r-squares are somewhat higher in the stepwise regression-based factor models. However, during the recent credit crisis, the differences between the three models have substantially increased.[4] Most importantly, the average monthly alpha from the FH seven-factor model amounts to a positive and insignificant 0.19% over all hedge funds included in our study (and is positive for 8 out of 11 strategies) and a negative -0.49% and -0.44% based on the FH eight-factor model and a stepwise regression-based model, respectively. Hence, while the FH seven-factor model generates comparable results (i.e., alphas) over "normal" and "bull market" states, the recently suggested extension as well as a stepwise regression-based approach generate much more pessimistic alpha estimates during the recent credit crisis. Over a second crisis period from June 1997 to April 1999, which includes the Asian currency crisis, the collapse of Long-Term Capital Management, and the Russian crisis, we again find a substantial difference

[3]Monthly return data on the PTFS factors can be obtained on the website of David Hsieh: http://faculty.fuqua.duke.edu/∼dah7/HFRFData.htm

[4]Khandani and Lo (2010) suggest summer 2007 as being the beginning of the crisis, because the sharp decrease of the S&P 500 index on August 9, 2007 forced many hedge fund managers to de-leverage their portfolios leading to large losses for highly leveraged hedge funds.

in alphas resulting from the FH model as compared to the SW and FH8 models.

A comparison of the FH eight-factor model and the model based on stepwise regression shows that both models generate qualitatively similar results, not only for emerging markets hedge funds but also for the majority of other hedge fund strategies (exceptions during the recent credit crisis being Convertible Arbitrage, Fixed Income Arbitrage, and Managed Futures funds). Hence, due to a much easier implementation, the FH eight-factor model seems to be a good choice for a broadly used factor model and a suitable successor for the widely used seven-factor model.

The remainder of the chapter is organized as follows. Section 4.2 describes the underlying data set and the methodology. Section 4.3 summarizes the results of the empirical analyses. Section 4.4 concludes.

4.2 Data and Methodology

4.2.1 Sample Selection and Data

Our sample includes all hedge funds included in the Lipper/TASS funds and CTA databases covering the time period from January 1994 to June 2009. We clean our sample for duplicate entries of specific hedge funds within and among the databases (e.g., due to multiple share classes and onshore and offshore vehicles of some funds as well as by double-counting of certain funds as Managed Futures fund and as CTA). We attempt to minimize the survivorship bias by including live and dead funds in our sample and restricting the sample period to the post-1993 period, when TASS started to keep all hedge funds which stopped reporting in the database. The backfilling bias is controlled for 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% of funds, we follow common practice and delete the first 12 return observations (e.g., Fung and Hsieh, 2000; Edwards and Caglayan, 2001).

To account for the fact that many hedge funds follow active trading strategies, we estimate alpha based on rolling 24-month window regressions. Therefore, 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 term “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-month history of returns, and find it to be very small. Furthermore, we exclude funds denoted in currencies other than USD and funds whose assets under management do not exceed USD 5 millions at least once during their non-backfilled observations. After all these adjustments, we are left with a sample of 3,846 hedge funds with total assets under management of USD 324bn per June 2009.[5]

The illiquidity of some of the markets in which the hedge funds are invested might have an influence on the reported returns. In order to adjust for the bias of these stale valuations, we follow the same approach as in Chapter 2 and desmooth the return series of our sample as suggested by Getmansky et al. (2004a).[6]

4.2.2 Measuring Hedge Fund Alpha

We measure hedge fund alpha based on the widely used seven-factor model of Fung and Hsieh (2004) and an extended version that additionally includes an eighth risk-factor, the MSCI emerging markets index return. The alpha based on the Fung and Hsieh (2004) seven-factor model is henceforth denoted as "alpha FH" and the alpha of the eight factor model "alpha FH8". We compare the results with a factor model in which we attempt to capture the different investment styles and to minimize the risk of omitted risk factors by using 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), Titman and Tiu (2008), and Ammann et al., (2010a, 2010b) and use the same forward stepwise regression approach for the selection of the risk factors to be included in our factor models as laid out in Section 2.3 in Chapter 2. We employ the identical risk factors for all funds within a strategy and keep them for the entire sample period. Henceforth, we label the alpha based on the stepwise regression approach "SW alpha". The complete set of factors considered for the selection procedure is listed in Appendix A, and the choice of factors resulting from the stepwise procedure for each strategy for the sample used in this chapter is reported in Table 4.1.

One major concern with the stepwise regression approach is that it is prone to data mining and may lead to an over-fitting in-sample while performing very poorly out-of-sample. However,

[5]When the assets of the 214 funds that have more than one series of shares and are therefore eliminated for calculating the equally-weighted indices are included in the sample, the assets under management increase to USD 347. According to the TASS Asset Flow Report of Q4, 2009 the hedge fund industry amounted to an estimated USD 1,090bn at the end of June 2009 (excluding funds of funds). Excluding the USD 80bn of funds of funds from our sample, but including the USD 23bn from different series of the funds, our sample therefore covers roughly one fourth of the total assets under management of the industry.

[6]Jagannathan et al. (2010) and Ammann et al. (2010a) find that this procedure of desmoothing the returns leads to a reduction of hedge fund alpha.

Table 4.1: Factor selection for each hedge fund strategy
The table reports the factors selected from a forward stepwise regression approach applied to equally-weighted strategy indices comprising our sample funds within each strategy. These risk factors are selected from 23 potential risk factors. The full choice of factors is provided in Appendix A. We require significance at the 5% level for factors be included (and 10% to remain) in the regression models.

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

** 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*

Ammann et al. (2010b) test the out-of-sample performance of their stepwise regression models by comparing the r-square obtained in out-of-sample regressions to those from in-sample regressions, where the stepwise approach was run over the same sample period as the subsequent alpha regressions, and they find that the average out-of-sample r-square is reasonably high and only slightly reduced as compared to the in-sample r-square. For comparison reasons, the average r-square from the FH model over the same time period is substantially lower than both the in-sample and the out-of-sample r-square from the stepwise models.

4.3 Empirical Analysis

Table 4.2 reports the alphas, t-statistics, and adjusted r-squares for the 11 strategy indices as estimated by the three alternative factor models. The last row of the table reports the average figures over all 11 strategies. "α FH", "t FH", and "FH $R^2_{(adj)}$" in the first three columns of the table indicate the alphas, t-statistics, and adjusted r-squares from the FH seven-factor model. "α FH8", "t FH8", and "t FH8" in Columns 4 to 6 indicate the alphas, t-statistics, and adjusted r-squares from the extended FH eight-factor model. "Δ SW" and "$t\,\Delta$ SW" in Columns 7 and 8 indicate the difference between the "α FH8" and "α SW" alphas and the t-statistic for the difference in means between these two alphas (where the means are calculated over the time series of rolling index alphas). "α FH8", "t FH8", and "FH8 $R^2_{(adj)}$" in Columns 9 to 11 indicate the alphas, t-statistics, and adjusted r-squares from the FH eight-factor model and "Δ FH8" and "$t\,\Delta$ FH8" in columns 12 and 13 indicate the difference between the "α FH8" and "α SW" alphas as well as the t-statistic for the difference in means between these two alphas. The last two columns provide information about the total cumulative return of each strategy index over the entire period (Rtrn %) as well as the total number of funds included for the estimation of the strategy indices (# Funds).

Most importantly, the results in Table 4.2 show that the average alpha over all 11 strategies is qualitatively similar for all three alternative factor models. On the strategy level, the differences are also rather small. Even for the emerging markets strategy index the results from the three alternative factor models are qualitatively similar and all alphas are positive and significant at the 1% level. However, both alphas and r-squares are somewhat higher for the FH8 and SW models that include an emerging markets factor.[7] In general, the benchmark (or risk) factors chosen by the stepwise approach are the hardest to beat by the hedge fund strategy indices. Nevertheless, 9 of the 11 strategy alphas from the SW model are positive and significant at the 1% level, one is negative and insignificant, and one is negative and significant at the 10% level. 10 of the 11 strategy alphas are positive and significant at the 1% level for the FH factor model, and all 11 are positive and significant for the FH8 model. Consequently, the difference between the alphas from the FH and the FH8 factor models is negative for eight and significant at the 5% level or better for three strategies. The difference between the alphas from the FH8 and the SW factor models is positive for nine and significant at the 10% level or better for seven strategies. Finally, the mean adjusted r-square over all strategies is 0.48 for the FH model and,

[7] The coefficients on the MSCI emerging markets factor is positive and highly significant with t-values of 37.8 and 52.3 in the SW and FH8 factor models, respectively. These coefficients on the risk factors are not reported for space reasons.

as expected, somewhat higher for the FH8 (0.57) and SW (0.59) models. Moreover, the addition of the emerging markets factor in the FH8 model does not only increase the adjusted r-square of the emerging markets strategy but for all 11 strategy indices (in fact, the highest percentage increases in the r-square of 60%, 55%, and 33% are observed for the strategies Equity Market Neutral, Emerging Markets, and Global Macro) indicating that various other strategies also invest heavily in emerging markets securities. Summarizing, the results in Table 4.2 show that the choice of the factor model has only a limited impact on the alpha estimate over the time period from January 1994 to June 2009, both on the strategy level as well as on average over all 11 strategies. Although statistically often significant, the differences in alphas are relatively small for most strategies (the most notable exceptions being Dedicated Short Bias and Long/Short Equity Hedge).

In Table 4.3, we repeat the analysis in Table 4.2 but split the sample into two sub-samples. The first sub-sample is reported in Panel A of the table and includes 57 months from January 1994 to September 1998 and the second sub-sample, reported in Panel B, includes the 129-month period from October 1998 to June 2009. The reason for using these two sub-periods is that Fung et al. (2008) find a structural break point in hedge fund returns after the collapse of Long-Term Capital Management in September 1998.[8] The results in Panel A again show similar results based on all three factor models both on the strategy level as well as on average over all strategies. The largest difference in absolute terms can be observed for the strategy Dedicated Short Bias. The alpha from the SW model is an insignificant 0.01% while the alphas from the FH and FH8 models are 1.46% and 2.54%, respectively, and highly significant. The reason for the very small alpha in the SW model is the very high exposure to the HML factor (the coefficient is 1.47 and the t-value 15.77), which is only included in this model. Hence, this strategy seems to invest heavily in value stocks, which perform very well during this time period. The difference in alphas between the FH and FH8 models of the Dedicated Short Bias strategy is due to a positive and highly significant coefficient on the emerging markets factor which performed poorly during this time period including the Asian and Russian crisis. Notable differences can also be observed for funds of funds and, not surprisingly, for emerging markets hedge funds. For both strategies, the alpha is positive and significant in the SW and FH8 factor models but negative and insignificant in the FH model. For both strategies the factor exposures on the MSCI emerging markets factor is positive and highly significant with t-values in excess of 10 (not reported for space space reasons). Given that the only difference between the FH

[8]This breakpoint is also confirmed by Naik et al. (2007), Meligkotsidou and Vrontos (2008), and Ammann et al. (2010a).

and FH8 models is this emerging markets factor and that the results from the FH8 and SW models are often similar, this emerging markets factor (which is also included in seven of the 11 strategies in the SW model) seems to be mainly responsible for the differences in the alpha estimates.

The results on the second sub-period in Panel B of Table 4.3 show similar results on an overall level. The average monthly alphas over the 11 strategies are 0.22%, 0.11%, and 0.04% for the FH, FH8, and SW models, respectively. However, there are more notable differences for certain strategies. Based on the FH model, the alpha of nine of the 11 strategies is positive and significant at the 5% level or better, the alpha of one strategy (Global Macro) is negative and insignificant, and the alpha of one strategy (Dedicated Short Bias) is negative and significant at the 1% level. For the FH8 model, eight alphas are positive and seven of those significant at the 1% level while the other three alphas (for the strategies Dedicated Short Bias, Fund of Funds, and Global Macro) are negative and significant at the 1% level. When using the SW model, only seven strategy alphas are positive, five of which are significant at the 5% level or better, while three of the remaining four (Dedicated Short Bias, Fund of Funds, and Global Macro) are negative and significant at the 5% level or better. While the alpha of the Dedicated Short Bias strategy index is negative and significant in all three factor models, the alpha of the Fund of Funds and Global Macro strategy indices are negative and significant only in the SW and FH8 factor models. As before, this difference can be explained by large and significant factor loadings on the emerging markets factor that is included in both the SW and FH8 factor models.

To investigate a potential time variability of these results, we display the rolling 24-month average strategy alpha over 10 strategies[9] as well as the rolling 24-month alpha of the emerging markets index over the complete time period from January 1996 to June 2009 in Figure 4.1.[10] Most importantly, both graphs show that the alphas obtained from the three alternative models are very similar over most sample years but that the alpha from the FH model substantially deviates from the other two models' alphas during the two crisis periods from June 1997 to April 1999 and from August 2007 to June 2009. During the first crisis period, the alpha from the FH model is substantially lower than that from the other two models. During this time period, the emerging markets factor had a high and negative cumulative excess return of -31.2% while the

[9] We exclude Dedicated Short Bias as this strategy only includes seven funds but the average alpha differs widely during the first crisis period from June 1997 to April 1999. The reason is that the SW model includes the HML factor, the VIX, and the SPX ATM Call option factor which are all highly significant (the HML and VIX factors positive and the SPX ATM Call factor negative). The large difference in the (positive) alpha estimates between the FH and FH8 factor models is due to a positive and significant factor loading on the emerging markets factor.

[10] As we estimate alpha over 24-month windows, we only have the first alpha observation after 23 months, i.e., in December 1995.

Table 4.2: Alphas of equally-weighted hedge fund strategy indices (January 1994 to June 2009)
The table reports the alphas estimated with three alternative factor models for 11 different hedge fund strategies, their corresponding t-statistics and the average adjusted r-squares of the models. The three factor models investigated include the Fung and Hsieh (2004) seven-factor model (FH), the FH model enhanced with an emerging markets risk factor (FH8), and a factor model that selects the risk factors based on forward stepwise regression (SW). Δ in Columns 7 and 12 represent the differences in means between the FH and FH8 models and between the FH8 and SW models. These figures are followed by their t-stats ($t\,\Delta$). Alphas are estimated 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. Rtrn (%) indicates the total cummulative return of each index over the period and # Funds the number of funds in the sample. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004a). Alphas are expressed in monthly percentage returns.

	FH			FH8					SW					Rtrn	#
	α	t	$R^2_{(adj)}$	α	t	$R^2_{(adj)}$	Δ	$t\,\Delta$	α	t	$R^2_{(adj)}$	Δ	$t\,\Delta$	(%)	Funds
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Convertible Arbitrage	0.42	13.62	0.35	0.49	13.71	0.40	-0.07	-1.43	0.31	7.94	0.59	0.18	3.47	175	117
Dedicated Short Bias	0.33	5.38	0.73	0.58	5.65	0.74	-0.25	-2.08	-0.08	-1.69	0.79	0.65	5.86	57	17
Emerging Markets	0.33	3.41	0.51	0.56	9.15	0.79	-0.24	-2.07	0.40	6.31	0.78	0.16	1.84	244	224
Equity Market Neutral	0.33	14.16	0.15	0.27	11.25	0.24	0.06	1.88	0.32	14.70	0.30	-0.05	-1.60	206	169
Event Driven	0.30	15.09	0.60	0.30	15.13	0.62	-0.00	-0.07	0.18	8.37	0.72	0.12	4.21	196	308
Fixed Income Arbitrage	0.27	10.42	0.26	0.27	8.70	0.29	-0.00	-0.10	0.23	9.87	0.22	0.04	0.95	156	113
Fund of Funds	0.04	1.37	0.57	0.14	4.44	0.73	-0.10	-2.30	-0.00	-0.13	0.73	0.14	3.27	102	808
Global Macro	0.24	3.66	0.39	0.23	3.11	0.52	0.01	0.10	0.20	3.11	0.50	0.03	0.29	300	144
Long/Short Equity Hedge	0.53	15.82	0.75	0.46	11.66	0.81	0.07	1.26	0.27	8.44	0.87	0.19	3.76	393	1,021
Managed Futures	0.45	10.57	0.48	0.46	10.52	0.51	-0.01	-0.10	0.31	6.75	0.49	0.14	2.29	423	799
Multi-Strategy	0.40	11.32	0.48	0.45	10.40	0.57	-0.05	-0.92	0.57	10.55	0.57	-0.11	-1.62	236	126
Average	0.33		0.48	0.38		0.57	-0.05		0.25		0.59	0.14		226	3,846

Table 4.3: Alphas of equally-weighted hedge fund strategy indices for two sub-periods

The table reports the alphas for the sub-period January 1994 to September 1998 (Panel A) and October 1998 to June 2009 (Panel B) estimated with three alternative factor models for 11 different hedge fund strategies, their corresponding t-statistics and the average adjusted r-squares of the models. The three factor models investigated include a factor model that selects the risk factors based on forward stepwise regression (SW), the Fung and Hsieh (2004) seven-factor model (FH), and the FH model enhanced with an emerging markets risk factor (FH8). Δ in Columns 7 and 12 represent the differences in means between the FH and FH8 models as compared to the SW model, respectively. These figures are followed by their t-stats ($t\,\Delta$). Alphas are estimated 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. # Funds indicates the number of funds in the sub-sample. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004a). Alphas are expressed in monthly percentage returns.

Panel A: Subperiod January 1994 to September 1998

	FH			FH8					SW					#
	α	t	$R^2_{(adj)}$	α	t	$R^2_{(adj)}$	Δ	$t\,\Delta$	α	t	$R^2_{(adj)}$	Δ	$t\,\Delta$	Funds
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Convertible Arbitrage	0.78	14.83	0.12	1.01	27.20	0.25	-0.22	-3.48	0.72	16.16	0.30	0.29	4.92	25
Dedicated Short Bias	1.46	11.23	0.34	2.54	9.87	0.41	-1.08	-3.75	0.01	0.12	0.52	2.53	8.91	6
Emerging Markets	-0.10	-0.54	0.25	1.40	13.89	0.52	-1.50	-7.05	1.10	8.37	0.51	0.30	1.83	68
Equity Market Neutral	0.82	37.84	-0.07	0.77	26.62	-0.07	0.05	1.38	0.79	36.31	0.03	-0.02	-0.65	18
Event Driven	0.24	5.72	0.30	0.36	8.98	0.30	-0.12	-2.10	0.30	5.05	0.39	0.06	0.87	63
Fixed Income Arbitrage	0.64	21.17	0.02	0.82	20.48	0.11	-0.18	-3.54	0.54	18.56	0.08	0.28	5.58	26
Fund of Funds	-0.09	-1.18	0.32	0.68	10.54	0.56	-0.76	-7.86	0.20	2.15	0.49	0.48	4.26	145
Global Macro	1.21	6.42	0.52	1.67	9.34	0.59	-0.47	-1.79	1.54	12.81	0.54	0.14	0.64	36
Long/Short Equity Hedge	0.84	13.51	0.43	0.97	20.80	0.45	-0.13	-1.70	0.72	11.94	0.60	0.25	3.28	197
Managed Futures	0.63	5.49	0.62	0.86	7.53	0.63	-0.23	-1.43	0.53	5.17	0.62	0.33	2.17	463
Multi-Strategy	0.71	5.94	0.19	1.19	12.06	0.32	-0.48	-3.13	1.44	11.77	0.33	-0.25	-1.60	23
Average	0.65		0.28	1.12		0.37	-0.47		0.72		0.40	0.40		1,070

Table 4.3 — continued
Panel B: Subperiod October 1998 to June 2009

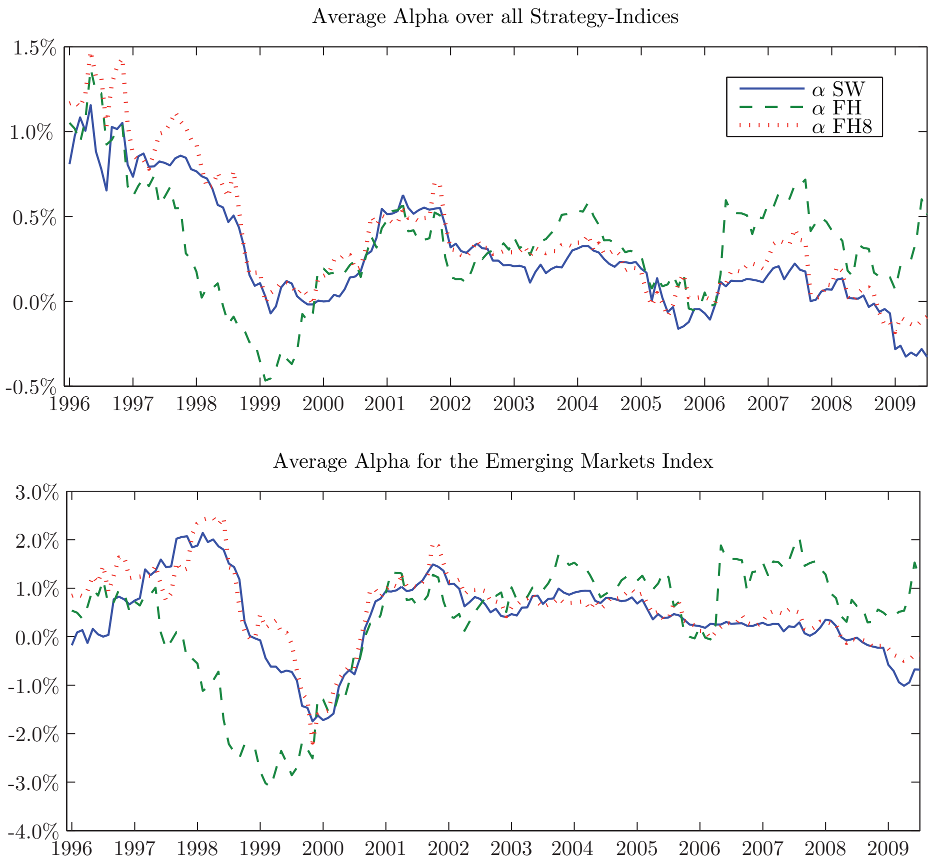
	FH			FH8					SW					#
	α	t	$R^2_{(adj)}$	α	t	$R^2_{(adj)}$	Δ	$t\,\Delta$	α	t	$R^2_{(adj)}$	Δ	$t\,\Delta$	Funds
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Convertible Arbitrage	0.24	5.45	0.35	0.24	5.37	0.37	-0.01	-0.13	0.05	0.96	0.63	0.20	2.93	114
Dedicated Short Bias	-0.13	-3.36	0.85	-0.14	-3.99	0.85	0.01	0.22	-0.30	-6.19	0.88	0.16	2.58	17
Emerging Markets	0.86	17.23	0.56	0.45	10.52	0.86	0.41	6.16	0.36	8.38	0.84	0.09	1.49	219
Equity Market Neutral	0.07	2.78	0.20	0.02	0.81	0.29	0.05	1.47	0.09	4.18	0.34	-0.07	-2.05	169
Event Driven	0.27	10.66	0.63	0.22	8.43	0.67	0.05	1.29	0.03	1.06	0.77	0.19	4.76	307
Fixed Income Arbitrage	0.18	9.11	0.30	0.14	6.44	0.31	0.04	1.41	0.15	8.25	0.27	-0.02	-0.55	111
Fund of Funds	0.07	2.16	0.61	-0.09	-3.12	0.76	0.16	3.69	-0.19	-4.64	0.76	0.10	2.01	795
Global Macro	-0.00	-0.06	0.41	-0.18	-4.95	0.59	0.17	2.80	-0.20	-5.41	0.57	0.03	0.54	143
Long/Short Equity Hedge	0.26	6.51	0.82	0.11	2.82	0.91	0.15	2.70	-0.02	-0.44	0.94	0.12	2.38	1,014
Managed Futures	0.39	6.36	0.41	0.29	4.81	0.44	0.10	1.18	0.18	2.60	0.41	0.11	1.17	675
Multi-Strategy	0.26	6.74	0.54	0.14	3.55	0.62	0.12	2.11	0.27	5.75	0.63	-0.13	-2.10	126
Average	0.22		0.52	0.11		0.61	0.11		0.04		0.64	0.07		3,690

majority of hedge funds (strategies) had a positive exposure on the emerging markets factor. In the second crisis, the alpha from the FH model is substantially higher than that of the SW and FH8 models. During this crisis period, the emerging markets factor again had a high negative cumulative excess return of -30.5% and all strategies load positively on this factor. However, the emerging markets factor captures a large part of the positive loading on the S&P 500 total return factor in the FH8 model for many strategies. As the return of the emerging markets factor is relatively higher than the return of the S&P 500 factor (-36.0%), adding the emerging markets factor leads to lower alphas in the FH8 model as compared to the FH model for the majority of strategies. In the SW model, the emerging markets factor, which is included in seven of the 11 strategies, captures a part of the exposures to other even worse performing factors, often the Russell 3000 index, with the same negative effect on the alpha. To summarize, many hedge fund strategy indices load positively on the emerging markets factor which in turn has experienced a very distinct performance from other factors during crisis periods. Therefore the neglect of this factor in a risk model substantially affects crisis alphas while the alpha in "normal" market states are less affected.

In Table 4.4, we repeat the analysis in Table 4.2 for the two crisis periods. The alphas for the first crisis period from June 1997 to April 1999 are reported in Panel A and the alphas for the second crisis period from August 2007 to June 2009 in Panel B. In Panel A, as expected from Figure 1, the average alpha over all strategies is -0.12% for the FH model which is substantially lower compared to the mean alphas from the SW (0.04%) and FH8 (0.31%) models. If we exclude the Dedicated Short Bias strategy, which only includes seven hedge funds but experiences extreme alpha differences between the different factor models, the mean crisis alphas over the remaining 10 strategies are -0.33% (FH), 0.18% (FH8), and 0.12% (SW). Hence, the difference between the SW and FH8 alphas is relatively small when the Dedicated Short Bias strategy is excluded while the alpha estimate resulting from the FH model is substantially lower confirming the findings in Figure 4.1. Panel B, also consistent with Figure 1, shows that during the second crisis period the average alpha from the FH model over all strategy indices is positive (0.19%) while the average alphas from the FH8 and SW models are -0.49% and -0.44%, respectively. On the strategy level, eight alphas based on the FH model are positive, two of which are significant. Only three alphas are negative and one of those significant. When using the SW alpha, nine alphas are negative, six of which are significant, and based on the FH8 model eight strategy alphas are negative, five of which are significant. As expected, in both panels the average r-square from the SW and FH8 models is higher than that of the FH model.

We perform a number of robustness tests on these results. First, we weight the funds within our

Figure 4.1: Alpha over time for all funds and Emerging Markets funds
The figure displays the mean alphas over 10 (Dedicated Short Bias is excluded) equally-weighted strategy indices (top part) as well as for the Emerging Markets strategy index (bottom part) over the entire sample period from January 1994 to June 2009. The alpha is estimated using a rolling 24-month regression based on the three different factor models. The three factor models investigated include the Fung and Hsieh (2004) seven-factor model (FH), the FH model enhanced with an emerging markets risk factor (FH8), and a factor model that selects the risk factors based on forward stepwise regression (SW). The indices are calculated based on desmoothed returns as proposed by Getmansky et al. (2004a) of all USD denominated funds with at least 24 non-backfilled observations. Alphas are expressed in monthly percentage returns.



strategies based on the assets under management instead of using equal weights. The respective results for the two crisis periods are reported in Table 4.5. As compared to Table 4.4, the results on the crisis from June 1997 to April 1999 are very similar (Panel A). The average alpha from the FH model is substantially lower than the alpha from the other two factor models. In Panel B, we note that the mean alpha across all strategies is substantially lower as compared to Table 4.4. This underperformance mainly stems from the strategy index Multi-Strategy, in which one large fund reported a return of -100%. In relative terms, however, we again find the FH alpha to be substantially larger than the alpha from the other two models. This also holds on most strategy levels with the exceptions of the strategies Equity Market Neutral, Managed Futures, and Multi-Strategy. Second, we calculate for each strategy the mean alpha over all individual funds within a strategy instead of constructing an index and the estimating the alpha of this index. The mean alphas are very similar to those in Tables 4.2 to 4.5 while the adjusted r-squares are generally lower (but also consistently higher for the SW and FH8 models as compared to the FH model). To save space, we do not report these results in a table. In the third robustness test, we use reported instead of desmoothed returns. This adjustment leads to a small decrease in the overall level of alphas and a slight increase in r-squares while our results remain qualitatively unchanged. Again, to save space we do not report this results in a table. As a final robustness test, we use 12-month and 36-month instead of 24-month rolling window regressions and find all our results to remain virtually unchanged. Therefore, these results are also not reported in a separate table.

4.4 Conclusion

This chapter contributes to the still ongoing discussion on which risk factor model to use to assess hedge fund performance. We compare the widely used Fung and Hsieh (2004) seven-factor model to a recently proposed extended eight-factor model and to a model that selects the risk factors based on a forward stepwise regression approach. Over a fairly long time period from 1994 to 2009, the alphas resulting from the three alternative factor models are qualitatively similar. However, during the recent credit crisis, we find a substantial difference in alphas resulting from the alternative models. Specifically, the average alpha from the FH model is positive (0.19% per month) while the alpha from the other two models is negative (-0.49% and -0.44%). Also on the strategy level, 8 out of 11 strategy alphas are positive based on the FH model while only two and three strategy alphas are positive when estimated with the other two factor models. We corroborate these findings based on another crisis period from June 1997 to April 1999, which includes the Asian currency crisis, the collapse of Long-Term Capital Management, and the Russian crisis. Again we find large differences in alphas resulting from the FH model as compared to the other two models. Both the stepwise and the eight-factor model generate qualitatively similar results even on the strategy level. Unlike the stepwise-based factor model, the eight-factor uses the same set of risk factors for all hedge fund strategies. Hence, given its much easier implementation, it seems to be a good choice for a broadly used factor model and a suitable successor for the widely used seven-factor model.

Table 4.4: Alphas of equally-weighted hedge fund strategy indices in crisis periods

The table reports the alphas for two different periods of crisis, i.e., June 1997 to April 1999 (Panel A) and September 2007 to June 2009 (Panel B) estimated with three alternative factor models for 11 different hedge fund strategies, their corresponding t-statistics and the average adjusted r-squares of the models. The three factor models investigated include the Fung and Hsieh (2004) seven-factor model (FH), the FH model enhanced with an emerging markets risk factor (FH8), and a factor model that selects the risk factors based on forward stepwise regression (SW). Δ in Columns 7 and 12 represent the differences in means between the FH and FH8 models and between the FH8 and SW models. These figures are followed by their t-stats. Alphas are estimated 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. Rtrn (%) indicates the total cummulative return of each index over the period and # Funds the number of funds in the sample. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004a). Alphas are expressed in monthly percentage returns.

Panel A: Subperiod June 1997 to April 1999

	FH			FH8			SW			Rtrn	#
	α	t	$R^2_{(adj)}$	α	t	$R^2_{(adj)}$	α	t	$R^2_{(adj)}$	(%)	Funds
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Convertible Arbitrage	0.28	1.50	0.69	0.47	2.06	0.70	0.34	2.33	0.86	17.38	27
Dedicated Short Bias	1.13	1.59	0.73	1.68	2.70	0.73	-0.55	-1.24	0.90	-7.20	7
Emerging Markets	-2.30	-2.18	0.62	0.15	0.22	0.88	-0.79	-0.71	0.85	-33.70	76
Equity Market Neutral	0.46	3.44	0.54	0.32	2.57	0.58	0.35	1.79	0.32	22.95	26
Event Driven	0.01	0.05	0.79	0.13	0.48	0.78	0.20	1.19	0.90	16.11	75
Fixed Income Arbitrage	-0.18	-0.56	0.26	-0.15	-0.38	0.21	-0.31	-0.67	0.18	2.71	32
Fund of Funds	-0.80	-2.32	0.65	-0.20	-0.61	0.76	0.32	1.14	0.83	7.16	174
Global Macro	-0.51	-1.00	-0.06	-0.30	-0.60	-0.10	-0.06	-0.15	-0.08	6.98	40
Long/Short Equity Hedge	0.72	3.93	0.88	0.71	3.12	0.87	0.55	1.94	0.92	38.51	230
Managed Futures	0.02	0.06	0.66	0.40	1.46	0.71	0.23	0.64	0.70	27.81	410
Multi-Strategy	-0.14	-0.64	0.62	0.16	0.60	0.66	0.11	0.35	0.58	11.94	28
Average	-0.12		0.58	0.31		0.62	0.04		0.63	10.06	1,125

Table 4.4 — continued
Panel B: August 2007 to June 2009

	FH			FH8			SW			Rtrn	#
	α	t	$R^2_{(adj)}$	α	t	$R^2_{(adj)}$	α	t	$R^2_{(adj)}$	(%)	Funds
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Convertible Arbitrage	1.07	2.39	0.69	0.51	0.99	0.70	-0.89	-2.23	0.60	-23.69	59
Dedicated Short Bias	0.39	1.15	0.73	0.28	0.91	0.71	0.01	0.02	0.83	54.93	9
Emerging Markets	0.85	1.38	0.67	-0.60	-1.96	0.93	-0.88	-2.16	0.91	-23.64	145
Equity Market Neutral	-0.38	-2.11	0.29	-0.52	-2.75	0.30	-0.20	-1.31	0.15	-3.50	92
Event Driven	0.06	0.29	0.73	-0.33	-1.48	0.79	-0.65	-5.63	0.87	-14.33	191
Fixed Income Arbitrage	0.20	1.01	0.84	0.02	0.09	0.85	-0.47	-2.71	0.78	-6.86	58
Fund of Funds	-0.15	-0.57	0.41	-0.88	-2.89	0.68	-2.27	-2.99	0.79	-15.16	581
Global Macro	0.51	1.79	0.09	-0.19	-1.17	0.75	-0.12	-0.43	0.67	14.91	72
Long/Short Equity Hedge	0.29	1.28	0.76	-0.37	-2.56	0.93	-0.35	-1.97	0.93	-11.14	566
Managed Futures	0.48	1.63	0.32	-0.17	-0.47	0.59	0.60	1.85	0.57	26.93	320
Multi-Strategy	-0.02	-0.10	0.50	-0.70	-2.64	0.75	-0.26	-1.41	0.66	-9.54	98
Average	0.19	0.81	0.53	-0.49	-2.50	0.82	-0.44	-1.87	0.78	-1.01	2,191

Table 4.5: Alphas of value-weighted hedge fund strategy indices in crisis periods

The table reports the alphas for two different periods of crisis, i.e., June 1997 to April 1999 (Panel A) and September 2007 to June 2009 (Panel B) estimated with three alternative factor models for 11 different hedge fund strategies, their corresponding t-statistics and the average adjusted r-squares of the models. The three factor models investigated include the Fung and Hsieh (2004) seven-factor model (FH), the FH model enhanced with an emerging markets risk factor (FH8), and a factor model that selects the risk factors based on forward stepwise regression (SW). Δ in Columns 7 and 12 represent the differences in means between the FH and FH8 models and between the FH8 and SW models. These figures are followed by their t-stats. Alphas are estimated over rolling 24-months windows. The table is based on value-weighted indices of all USD denominated funds with at least 24 non-backfilled observations for each strategy. Rtrn (%) indicates the total cummulative return of each index over the period and # Funds the number of funds in the sample. The returns are desmoothed based on the procedure proposed by Getmansky et al. (2004a). Alphas are expressed in monthly percentage returns.

Panel A: Subperiod June 1997 to April 1999

	FH			FH8			SW			Rtrn	#
	α	t	$R^2_{(adj)}$	α	t	$R^2_{(adj)}$	α	t	$R^2_{(adj)}$	(%)	Funds
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Convertible Arbitrage	0.56	2.24	0.69	0.89	4.29	0.76	0.65	4.05	0.82	27.16	27
Dedicated Short Bias	0.84	1.91	0.83	1.15	3.19	0.82	-0.13	-0.61	0.93	-4.57	7
Emerging Markets	-2.07	-1.44	0.58	0.93	0.76	0.78	-0.47	-0.24	0.70	-40.80	76
Equity Market Neutral	0.52	6.33	0.37	0.44	4.63	0.38	0.44	3.17	0.19	22.97	26
Event Driven	0.16	1.10	0.78	0.34	2.05	0.78	0.43	2.84	0.86	18.08	75
Fixed Income Arbitrage	-0.45	-1.25	0.18	-0.28	-0.66	0.14	-0.49	-0.99	0.14	-1.18	32
Fund of Funds	-0.76	-2.03	0.67	-0.47	-1.17	0.66	0.44	1.07	0.74	19.10	174
Global Macro	-2.12	-1.62	0.15	-1.91	-1.52	0.09	-0.72	-0.64	0.14	-6.51	40
Long/Short Equity Hedge	0.70	2.48	0.79	0.68	1.98	0.77	0.64	1.82	0.88	43.06	230
Managed Futures	0.03	0.09	0.60	0.49	1.55	0.67	0.11	0.32	0.65	26.95	410
Multi-Strategy	-0.70	-1.82	0.53	-0.39	-0.82	0.54	0.28	0.60	0.50	16.87	28
Average	-0.30		0.56	0.17		0.58	0.11		0.60	11.01	1,125

Table 4.5 — continued
Panel B: August 2007 to June 2009

	FH			FH8			SW			Rtrn	#
	α	t	$R^2_{(adj)}$	α	t	$R^2_{(adj)}$	α	t	$R^2_{(adj)}$	(%)	Funds
Strategy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Convertible Arbitrage	0.44	1.28	0.50	-0.01	-0.02	0.51	-0.72	-2.34	0.66	-17.14	59
Dedicated Short Bias	0.44	1.28	0.75	0.27	0.82	0.74	0.07	0.12	0.83	59.04	9
Emerging Markets	0.89	1.59	0.61	-0.44	-1.49	0.90	-0.76	-1.67	0.86	-16.66	145
Equity Market Neutral	-1.23	-1.72	0.47	-0.18	-0.26	0.54	-0.16	-0.22	-0.08	-35.65	92
Event Driven	-0.11	-0.49	0.59	-0.53	-2.37	0.71	-0.55	-4.39	0.77	-11.95	191
Fixed Income Arbitrage	0.33	1.16	0.63	0.01	0.04	0.67	-0.41	-1.58	0.67	-3.46	58
Fund of Funds	-0.16	-0.60	0.42	-0.80	-2.76	0.65	-2.32	-2.55	0.72	-13.79	581
Global Macro	0.67	2.05	-0.12	0.04	0.13	0.22	0.00	0.01	0.32	18.96	72
Long/Short Equity Hedge	0.42	1.99	0.54	-0.27	-1.33	0.81	-0.20	-0.93	0.86	-4.24	566
Managed Futures	0.14	0.60	0.25	-0.42	-1.32	0.53	0.42	1.49	0.53	17.01	320
Multi-Strategy	-1.59	-3.19	0.70	-2.23	-3.00	0.76	-0.77	-1.91	0.48	-29.89	98
Average	0.02		0.49	-0.41		0.64	-0.49		0.60	-3.43	2,191

Chapter 5

Conclusion

The amount of capital invested in the hedge fund industry has significantly increased since 1994. According to the TASS Asset Flow Report, the assets under management by hedge funds (excluding funds of funds) are estimated to have increased from roughly USD 50bn in January 1994 to USD 1,090bn in June 2009, with a peak of 1,546bn in June 2007, corresponding to an average annual growth rate of 22%. The change in size of this asset class makes research on hedge fund performance more relevant and, due to the improved availability of data, also more reliable. For these reasons, this doctoral thesis is dedicated to three aspects of this broad area of research.

A plausible consequence of the increased competition in the hedge fund industry is a decrease in 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 to diversify to other strategies, where their knowledge and experience might be limited. There might be only a limited dollar amount of alpha in the market to be shared among more hedge funds. In fact, a recent stream of literature provides empirical evidence consistent with this line of reasoning. Specifically, these studies suggest that hedge fund alpha has been decreasing over time, in particular from 2000 to 2004. Moreover, these studies document increasing capital inflows into the industry over the same time period and conclude that the declining alpha is due to decreasing returns to scale caused by capacity constraints and/or unscalability of managers' skills.

Chapter 2 of this thesis contributes to the existing literature by investigating hedge fund alpha based on a recent and comprehensive data set compiled from Lipper/TASS covering the time period from January 1994 to September 2008. We employ two alternative factor models to assess hedge fund performance. In the first factor model, we select the risk factors based on a stepwise regression approach attempting to determine the statistically optimal combination of risk factors to be included in the factor model. We compare the results from this stepwise regression approach to those obtained by the widely used seven-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 time-varying benchmark for the returns of equally-weighted and value-weighted hedge fund strategy indices and single hedge funds.

Our results indicate that hedge fund alpha has been positive on average irrespective of the underlying factor model. In addition, and unlike previous research, we find no systematically decreasing alpha in the hedge fund industry over time. Moreover, we find no evidence pointing to capacity constraints in the hedge fund industry over the full time period from 1994 to 2008. While the findings over the time period from 1994 to 2001 are consistent with prior research and suggest capacity constraints at the single fund level, the results for the more recent sub-period from 2002 to 2008 show a positive relationship between fund flows and future alpha. Consequently, our results suggest that there are either no capacity constraints at the single hedge fund level or that such capacity constraints are time-varying.

The second topic of this thesis investigates performance persistence of hedge funds. Although a large number of papers have been published on the performance persistence of hedge funds, no common consensus has yet been found on whether hedge fund performance persists or not. The majority of papers find short-term persistence but there is only little support for long-term persistence. However, in light of notice and redemption periods, the knowledge about short-term performance persistence of hedge funds does not add a great deal of value for an investor. Therefore, Chapter 3 focuses on long-term performance persistence over time horizons of 6 to 36 months and we attempt to form hedge fund portfolios that consistently outperform their peers.

We use a merged sample from the Lipper/TASS and CISDM databases covering the time period from 1994 to 2008. Unlike previous studies, we investigate the performance persistence of two-way sorted portfolios, for which the sorting is based on past performance and various additional fund characteristics. To assess hedge fund performance, 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). The dynamics in the factor exposures are accounted for by using a rolling-window regression approach. Moreover, in this chapter we focus on the investment performance of sorted portfolios instead of investigating the statistical significance of hedge fund performance persistence only. We find alpha persistence of up to three years which is both economically and statistically highly significant. The difference in monthly alpha based on a stepwise regression model between the quintile-portfolio consisting of the historically best performing hedge funds and the quintile-portfolio consisting of the historically worst performing hedge funds amounts to a statistically significant and economically sizeable 2.80% monthly alpha for 6-month rebalancing horizons, 2.29% for 12-month rebalancing horizons, 1.61% for 24-month rebalancing horizons, and 0.99% for 36-month rebalancing horizons. Persistence in raw returns is economically substantial for time horizons of up to two years but statistically significant only over a six-month horizon.

We then attempt to further improve the performance persistence by identifying fund characteristics that are related to the probability of exhibiting performance persistence. We estimate panel probit regressions of an indicator variable for whether a fund exhibits performance persistence on a number of fund characteristics. The fund characteristics we include in this analysis include fund size, fund age, relative fund flows, a dummy variable whether the fund is closed to new investments, the length of the notice and the length of the redemption period, management and incentive fees, leverage, a dummy variable for whether the fund management is personally invested in the fund, and a 'Strategy Distinctiveness Index' (SDI) as originally suggested by Wang and Zheng (2008). This SDI attempts to measure manager skills and the uniqueness of the hedge funds' trading strategies. The results from the probit analysis show that all these fund characteristics are significantly related to the probability of observing performance persistence. However, by using two-way sorts and forming hedge fund portfolios not only based on the funds' historical alpha but also on one of these fund characteristics, we find only the SDI to have the ability to systematically improve performance persistence. We find such an improvement in alpha over time horizons up to two years and ranging between 12 and 31 basis points per month. Our results are robust with respect to the factor model we use for measuring hedge fund alpha, the benchmark we use for calculating the SDI, the quantiles used to form portfolios (i.e., median, tercile, quartile, and quintile), and whether the analysis is based reported returns or returns which are adjusted for a potential return smoothing, for example due to illiquidity of the invested assets. Only during the credit crisis of 2008, the positive contribution of the SDI disappears indicating that high-SDI funds may take on larger idiosyncratic risks that show up in lower (systematic) risk-adjusted returns (i.e., alphas) during crisis periods.

Chapter 4 contributes to the ongoing discussion on which risk factor model to be used to assess hedge fund performance. Based on a sample that includes all hedge funds from the Lipper/TASS funds and CTA databases covering the time period from January 1994 to June 2009 we compare three alternative factor models: The widely used Fung and Hsieh (2004) seven-factor model, a recently proposed extension to an eight-factor model, and a model that selects the relevant risk factors based on a forward stepwise regression approach. In the sample from 1994 to 2009, the alphas resulting from the three alternative factor models are qualitatively similar over fairly long time periods. However, during the recent credit crisis, we find a substantial difference in the alphas resulting from the Fung and Hsieh (2004) seven-factor model compared to the other two models. Specifically, the average alpha from the Fung and Hsieh (2004) seven-factor model is positive (0.19% per month) while the alpha from the other two models is negative (-0.49% and -0.44%). On the strategy level, 8 out of 11 strategy alphas are positive based on the Fung and Hsieh (2004) seven-factor model, while the other two factor models yield only two and three positive strategy alphas, respectively. We corroborate these findings based on another crisis period from June 1997 to April 1999, which includes the Asian currency crisis, the collapse of Long-Term Capital Management, and the Russian crisis. Again we find large differences in alphas resulting from the Fung and Hsieh (2004) seven-factor model as compared to the other two models. Hence, the emerging markets factor, which is included in the eight-factor model and is chosen by the stepwise-based model in 7 out of 11 hedge fund strategies, seems to capture a large part of hedge fund return volatility during crisis periods. Both the stepwise and the eight-factor model generate qualitatively similar results even on the strategy level. Unlike the stepwise-based factor model, the eight-factor model uses the same set of risk factors for all hedge fund strategies. Hence, given its computationally simpler implementation, it seems to be a good choice for a broadly used factor model and a suitable successor for the widely used seven-factor model.

Summarizing, this thesis we finds that positive hedge fund alpha has been existing over time, when all fees and potential biases in reported hedge fund returns are accounted for. We fail to identify a clear time pattern of the alpha. Most importantly, we find no evidence that the average alpha has been decreasing over time. We find a positive average hedge fund alpha irrespectively of the choice of the factor model. Only in extraordinary circumstances, as in crisis periods, do the different factor models reveal significantly different alpha estimates. Furthermore, the knowledge about historical alpha and other fund characteristics enables investors to form hedge fund portfolios that, statistically and economically highly significantly, outperform their peers.

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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)[1], Black Scholes S&P 500 ATM/OTM call and put options 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[2]
- **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)

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

[2] 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.

Curriculum Vitae

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