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WHY DOES HEDGE FUND ALPHA DECREASE OVER TIME?
EVIDENCE FROM INDIVIDUAL HEDGE FUNDS

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Abstract

Why has the aggregate level of hedge fund alpha (risk-adjusted return) decreased over the last decade? By studying the distribution of individual hedge fund alphas, we find that the large right tail (the percentage of funds with positive alphas) that was once present has shrunk over time, while the left tail (the percentage of funds with negative alphas) has remained unchanged. Thus, the decrease in average alpha is not due to an increasing proportion of funds with unskilled managers and negative alphas, as the hedge fund bubble hypothesis suggests. Instead, it is due to a decrease in the proportion of funds that are capable of producing large positive alphas. Our evidence is consistent with the predictions of the capacity constraint hypothesis. Using quantile regression and counter-factual density analysis, we show that both the changes in fund characteristics and the changes in market conditions from the 1990s to the 2000s contribute to the decrease in the proportion of funds with positive alphas. Furthermore, we find that fund-level flow has a positive (negative) impact on a fund's future performance for smaller (larger) funds, while strategy-level flow (flow into the strategy to which a fund belongs) always has a negative impact on the fund's future performance. Our results suggest that the economic reasons for capacity constraints arise both from the "unscalability" of managers' abilities and from the limited profitable opportunities in the market.

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Chapter 1

Introduction

1.1 The Search for Hedge Fund Alpha

In the fast-growing hedge fund industry, the search for alpha (risk-adjusted return) is the most important task of fund managers. In addition, the debate over the existence of alpha is an important topic in academic research on hedge funds. Previous studies show that hedge funds have higher Sharpe ratios than mutual funds [Ackermann, McEnally, and Ravenscraft (1999) and Liang (1999)], that hedge fund performance is persistent [Brown, Goetzmann, and Ibbotson (1999), Agarwal and Naik (2000b), Edwards and Caglayan (2001), Capocci and Hübner (2004), and Kosowski, Naik, and Teo (2007)], that hedge funds employ dynamic trading strategies and have non-linear option-like payoffs [Fung and Hsieh (1997), Agarwal and Naik (2000a)], Fung and Hsieh (2001), Mitchell and Pulvino (2001), Brooks and Kat (2002), and Agarwal and Naik (2004)], and that hedge funds deliver significant alphas, even after being controlled for non-linear factors [Fung and Hsieh (2004b) and Kosowski, Naik, and Teo (2007)]. Therefore, private investors and intuitional investors have been fascinated by the seemingly unlimited source of "alternative investments" that the rapid expansion of the hedge fund industry provides. Yet, as an increasing number of new investments are drawn into the hedge fund industry, a concern about the sustainability of hedge fund alpha has emerged. Recent academic research demonstrates that the overall level of alpha has been in decline through the past decade. [See Fung, Hsieh, Naik, and Ramadorai (2008) for the evidence from (hedge) funds-of-funds and Naik, Ramadorai, and Stromqvist (2007) for the evidence from eight broadly defined hedge fund strategies.]

1.2 Contributions of this Thesis

1.2.1 Hedge Fund Bubble Hypothesis versus Capacity Constraint Hypothesis

The first contribution of this thesis is to explain why hedge fund alpha has decreased over time. In order to accomplish this task, this thesis will test two alternative hypotheses: the hedge fund bubble hypothesis and the capacity constraint hypothesis. While prior research has focused on the aggregate level of alpha (alpha of average hedge fund return), this thesis examines the alphas of individual hedge funds. Studying individual hedge funds yields insights into many unanswered questions.

The advantage of using individual hedge fund data is that it allows us to delimit precisely which kinds of hedge funds are responsible for the decrease in average alpha. Two alternative hypotheses have been proposed in the literature. The first one is the "hedge fund bubble" hypothesis, which argues that the lucrative compensation structure of hedge funds has attracted managers who possess only marginal ability (or no ability at all) to enter the hedge fund industry.[1] Therefore,

[1] The fee structure for a typical hedge fund is comprised of a 2% management fee plus a 20% incentive fee.

the increasing percentage of "bad" managers (whose funds will most likely have negative alphas due to the lack of superior ability and the imposition of hedge fund fees) is the reason for the decline in average alpha. In distinction to this hypothesis, the "capacity constraint" hypothesis attributes the decline in alpha to the increase of total assets under management (AUM) in the hedge fund industry. Due to the effect of diminishing returns to scale, the increase in AUM over the last decade has led to a decline in the proportion of those "good" managers who were once able to produce large positive alpha.

By evaluating the evolution of the distribution of individual hedge fund alphas, we can examine these two hypotheses. If the increasing percentage of bad managers explains the decline in overall alpha, then the left tail of the distribution (the percentage of funds with negative alphas) should expand over time, leading to a decline in the mean-level of alpha. On the other hand, if the disappearance of alpha-producing funds is the actual cause, then the right tail of the distribution (the percentage of funds with positive alphas) would shrink over time, resulting in a decrease in average alpha.

1.2.2 Disentangling the Economic Reasons for Capacity Constraints

This thesis will also investigate the economic reasons for the observed capacity constraints in the active asset management industry. Previous studies have documented the existence of capacity constraints in the mutual fund industry by using fund-level data [Berk and Green (2004) and Chen, Hong, Huang, and Kubik (2004)]. Because of the special nature of hedge fund management, it is likely that capacity constraints play an even larger role in the hedge fund industry than in the mutual fund industry. Yet, the extant literature on hedge funds only examines capacity constraints by using either strategy returns [Naik, Ramadorai, and Stromqvist (2007)] or funds-of-funds returns [Fung, Hsieh, Naik, and Ramadorai (2008)]. Our analysis of individual hedge funds is a natural extension of the work done by Berk and Green (2004) and Chen, Hong, Huang, and Kubik (2004). Furthermore, examining individual hedge fund data facilitates the exploration of economic reasons behind the capacity constraints in active asset management.

General consensus maintains that the production of hedge fund alpha depends upon two elements: (1) the existence of profitable (arbitrage) opportunities in the market, and (2) the ability of hedge fund managers to locate and capitalize on these opportunities. Therefore, there are two alternative economic reasons for the observed capacity constraints: (1) limited profitable opportunities (i.e., a fixed number of profitable opportunities available for a given strategy), and (2) the "unscalability" of managers' abilities (i.e., the constraint on the size of hedge fund that a fund manager can handle without sacrificing performance). Although the extant literature on the negative relation between the average alpha and the aggregate strategy flow indicates the existence of capacity constraints in the hedge fund industry, it is silent on the underlying economic reasons for such constraints. By studying individual hedge fund data, we can disentangle these alternative explanations using some specially-designed methodologies.

First, we adopt the method of counter-factual density analysis, which decomposes the change in distribution of individual hedge fund alphas into two effects—the difference in fund characteristics between two sub-sample periods, and the change in market conditions from 1990 to the present. If the unscalable ability of hedge fund managers is the main cause of capacity constraints, then any observed change in distribution of hedge fund alphas should be explained by the difference in fund characteristics (such as size, leverage, compensation structure, etc.) between funds in the 1990s and funds in the 2000s. On the other hand, if limited profitable opportunities are the source of constraints, then we will find that even the funds with the same characteristics as their successful counterparts in the 1990s will not be able to produce positive alphas in the market conditions of the 2000s.

Second, we extend the traditional regression-based method to include both individual fund-level flow and strategy-level flow (flow into the strategy to which a fund belongs). If the unscalability of managers' abilities is the driving force for capacity constraints in the hedge fund industry, then there should be a negative relationship between fund-level flow and each fund's future performance. On the other hand, if limited profitable opportunities are the main reason for capacity constraints in the hedge fund industry, then we will find that strategy-level flow has a negative impact on individual fund's future performance, even for those funds without expansion in AUM.

1.3 Summary of Empirical Results

Based on a hedge fund database that covers more than 8,000 existing and defunct individual hedge funds or funds-of-funds, we find that the performance difference between the good and the bad funds (as measured by either return or alpha[2]) becomes smaller over time. Comparing the empirical distribution of hedge fund alpha from the last few years with the distribution from the mid-1990s, our research reveals that the large right tail of the distribution (the percentage of funds with positive alpha) that was once present has shrunk, while the left tail of the distribution (the percentage of funds with negative alpha) has remained unchanged.

[2]The results reported in this thesis are based on the seven-factor model developed by Fung and Hsieh (2004b).

These findings indicate that the decrease in the overall level of alpha is not due to an increasing proportion of funds with negative alphas, as suggested by the hedge fund bubble hypothesis. Instead, it is due to the decrease in the proportion of funds capable of producing large positive alphas. Our evidence provides support for the capacity constraint hypothesis.

Using counter-factual density analysis to examine the observed change in distribution, we show that both the change in fund characteristics (e.g., the growing size of individual funds) and the change in market conditions (e.g., the increasing competition for the limited profitable opportunities available in the market) are responsible for the decrease in the proportion of funds with positive alphas. These results suggest that the economic reasons for capacity constraints arise both from the unscalability of managers' abilities and from the limited profitable opportunities.

Finally, analysis of the linkage between individual hedge fund alpha and fund-level (strategy-level) flow reveals several interesting results and provides further evidence for the economic sources of capacity constraints: (1) fund-level flow has a positive (negative) impact on a fund's future performance for smaller (larger) funds; (2) strategy-level flow (flow into the strategy to which a fund belongs) always has a negative impact on the fund's future performance; and (3) there is significant cross-sectional variation in the impact of capacity constraints on both funds in different strategies and funds with different characteristics. Again, our results confirm the existence of constraints arising from both the unscalability of managers' abilities and the limited profitable opportunities in the market.

1.4 Structure of this Thesis

The rest of the thesis is organized as follows: Chapter 2 provides a literature review of hedge fund research. Chapter 3 describes the hedge fund data used in this study. Chapter 4 discusses the research methodology applied in this thesis. Chapter 5 presents empirical findings. In Chapter 6, we explore various robustness checks, and we conclude in Chapter 7.

Chapter 2

Literature Review

2.1 History of the Hedge Fund Industry

It is generally believed that the history of hedge funds dates back as far as 1949, when Alfred Winslow Jones started the first hedge fund.[1] Jones's innovative idea was to take both long and short positions in stocks to "hedge" against market risk. The success of such a strategy relied on a manager's superior ability to identify over-valued or under-valued stocks, and not on his ability to predict the movement of the overall market. In addition, Jones utilized the proceeds from short sales to finance the long position, essentially adding leverage to his portfolio. To attract investors, Jones used a compensation structure of performance-linked fees.

Since its inception over fifty years ago, however, the term "hedge fund" has evolved to a point at which there is no universally accepted definition of a typical hedge fund. In fact, today's hedge fund industry consists of thousands of heterogeneous funds that use a variety of strategies, each of which differs greatly. Fortunately, most hedge funds share a number of common characteristics that are distinguishable from other conventional investment vehicles, such as mutual funds.

[1] See Lhabitant (2002) for a more detailed account of the history of hedge funds.

Hedge funds are generally regarded as private investment vehicles for wealthy individuals and institutional investors with very high minimal investment requirements. Hedge funds are often structured as limited partnerships, with general partners being the portfolio managers who make investment decisions. Furthermore, hedge funds can be identified by their exemption from government regulations (e.g., the Investment Company Act of 1940) and their performance-linked compensation structure. Managers of hedge funds seek to add value to their portfolios through investment in non-traditional assets, active management of dynamic trading strategies, and the use of leverage. The success of such strategies often requires fund managers to adopt provisions to limit the flexibility of share subscription and redemption, such as an initial lock-up period and special redemption requirements.[2] In return, hedge fund managers seek to achieve abnormal risk-adjusted returns for their investors.

The hedge fund industry was traditionally only available to wealthy individuals, and had remained relatively small before the 1990s. However, the industry experienced tremendous growth throughout the 1990s and the early 2000s both in terms of assets under management (AUM) and the number of funds.[3] An important reason for such rapid development is the increasing interest from institutional investors searching for alternative investment opportunities. Consequently, institutional investors have achieved a great prominence in the industry's clientele. Both the increased popularity and the change of clientele have produced higher demand for more rigorous research on hedge funds. However, due to the lack of publicly available data, the hedge fund industry had stayed opaque to the general public

[2]Lock-up period is the minimum time that an investor is required to wait before being allowed to redeem his or her shares. Redemption requirements include the terms and conditions (e.g., an advanced notice requirement) that investors have to follow to redeem their shares.

[3]Hedge Fund Research Industry Reports estimate the total AUM of the hedge fund industry to be over $1.8 trillion at the end of 2007.

until the late 1990s, when rigorous academic research on hedge funds started to emerge. In the following sections, we will provide a brief overview of the growing body of hedge fund research.[4]

2.2 Research on Hedge Fund Risk and Return

To overcome the difficulty of directly analyzing the risk and return trade-off of hedge funds, the earliest research from the late 1990s compares the performance of hedge funds with those of traditional investment vehicles, such as mutual funds. Using a sample of 281 hedge funds from Hedge Fund Research, Inc. (HFR), Liang (1999) finds that, on average, hedge funds had both higher returns and higher risks than mutual funds for the sample period of 1992 to 1996. The average monthly return for hedge funds was 1.10%, compared to 0.85% for mutual funds. The standard deviation of monthly returns for hedge funds was 2.40%, versus 1.91% for mutual funds. In addition, the average Sharpe ratio (the ratio of excess return to the excess return's standard deviation) for hedge funds was 0.44, which is higher than the 0.26 average Sharpe ratio for mutual funds. Similarly, using monthly returns of 547 funds from a combination of both Managed Account Reports, Inc. (MAR) and HFR, Ackermann, McEnally, and Ravenscraft (1999) find that the average Sharpe ratio of hedge funds was higher than that of mutual funds for the 2-, 4-, 6-, 8-year sample periods ending in December 1995. Furthermore, hedge funds dominated mutual funds in every region (U.S., international, and global).

While the Sharpe ratio is one of the most commonly employed risk-adjusted measures, some studies have shown that it can be manipulated by the use of option-

[4]See Agarwal and Naik (2005) and Fung and Hsieh (2006) for more extensive literature reviews on hedge fund research.

like strategies.[5] [See, for example, Lhabitant (2000) and Goetzmann, Ingersoll, Spiegel, and Welch (2006)]. This could lead to potentially serious problems, since a large group of research has shown that hedge fund payoffs are nonlinear [Fung and Hsieh (2001), Mitchell and Pulvino (2001), Brooks and Kat (2002), and Agarwal and Naik (2004)].

The process of generating hedge fund returns has been shown to be much more complex than that of traditional investment vehicles [Fung and Hsieh (1997), and Agarwal and Naik (2000a)]. Fung and Hsieh (1997) argue that the returns of hedge fund managers should be characterized by three elements: where they trade (the assets they invest in), how they trade (the trading strategies employed), and how the positions are financed (the use of leverage). Due to their use of dynamic trading strategies, hedge funds could potentially contain certain systematic risks that are not observable in the context of a linear-factor model with standard asset benchmarks. This is indeed what has been found in the literature. Fung and Hsieh (2001) use option lookback straddles to model trend-following strategies, and show that these strategies can explain the returns of trend-following funds better than standard asset indexes. Mitchell and Pulvino (2001) find that the returns of merge and acquisition (M&A) arbitrage are similar to those obtained from selling uncovered index put options. Brooks and Kat (2002) show that the published hedge fund indexes exhibit relatively low skewness and high kurtosis. Agarwal and Naik (2004) characterize the systematic risk exposures of hedge funds using both buy-and-hold and option-based strategies, and show that a large number of equity-oriented hedge funds' strategies exhibit payoffs resembling those of a short position in the Standard and Poor's (S&P) 500 index put option.

[5]This is because Sharpe ratio only considers the first and second moments of the returns, and option-like strategies can alter the shape of the probability distribution of returns to the extent that higher moments are manipulated.

Given the problems associated with using a linear-factor model with standard asset benchmarks to measure hedge fund performance, Fung and Hsieh (2002b) propose a bottom-up approach, which starts with using traded assets to construct "asset-based" benchmarks (called ABS factors) to explain the returns of hedge funds in each specific strategy. A number of studies have adopted this approach and found a variety of ABS factors for different strategies. For example, Fung and Hsieh (2001) model the returns of managed futures funds using option straddles of stocks, bonds, interest rates, currencies, and commodities. Mitchell and Pulvino (2001) track the returns of M&A arbitrage funds to a passive merge arbitrage strategy based on announced mergers. Fung and Hsieh (2002a) show that fixed income hedge funds typically have exposure to interest rate spreads, such as credit spreads, mortgage spreads, etc. Agarwal and Naik (2004) link the returns of equity-oriented hedge funds to S&P 500 options. Fung and Hsieh (2004a) show that long-short equity hedge funds have positive exposure to both the overall stock market and a small-cap-minus-large-cap factor, which is similar to the SMB factor in the Fama-French three-factor model [Fama and French (1992) and Fama and French (1993)]. Using data on Japanese and U.S. convertible bonds and their underlying stocks, Agarwal, Fung, Loon, and Naik (2005) study the returns of convertible arbitrage funds. Duarte, Longstaff, and Yu (2007) replicate the returns of commonly used strategies of fixed-income funds using observable prices of various fixed-income securities and derivatives.

Based on the ABS factors of major hedge fund styles found in the empirical studies, Fung and Hsieh (2004b) propose a basic risk-factor model that can be used to model hedge fund returns in general. They find that a large portion of hedge fund returns can be explained by the returns of four traditional buy-and-hold strategies and three primitive trend-following strategies (PTFS) constructed from option prices.[6]

2.3 Research on Hedge Fund Alpha

In light of the emphasis on alpha by institutional investors (who have overtaken wealthy individuals as the primary hedge fund investors), studies on hedge fund alpha, which measures the excess returns of hedge funds over some appropriate benchmarks, comprise a strand of growing literature. The early empirical evidence regarding the ability of hedge fund managers to deliver alpha appears to be quite promising.

Using annual data from the U.S. Offshore Funds Directory for a sample period of 1989 to 1995, Brown, Goetzmann, and Ibbotson (1999) find positive Jensen's Alphas for all hedge fund strategies except for short-sellers. Using data from MAR and HFR, Ackermann, McEnally, and Ravenscraft (1999) show that annualized Jensen's alphas for hedge funds are significantly positive and range from 6 percent to 8 percent in most of the sub-sample periods from 1988-1995. Using HFR data from 1992-1996, Liang (1999) applies stepwise regression of an eight-asset-class factor model and finds that seven out of sixteen equally weighted hedge indexes produce significant and positive alphas. Using MAR data from 1990-1998, Edwards and Caglayan (2001) examine the alpha of a six-factor model, and find that 25% of hedge funds earn positive alphas. Using data from a combination of the Center for International Securities and Derivatives Markets (CISDM), HFR, Morgan Stanley Capital International (MSCI), and Lipper TASS (TASS) for the sample period of

[6]The seven factors include the S&P 500 return minus risk-free rate (SNPMRF), Wilshire small cap return minus large cap return (SCMLC), change in the 10-year treasury constant maturity yield (BD10RET), change in the Moody's Baa yield less 10-year treasury constant maturity yield (BAAMTSY), the return of bond primitive trend-following strategy (PTFSBD), the return of currency primitive trend-following strategy (PTFSFX), and the return of commodity primitive trend-following strategy (PTFSCOM).

1994-2002, Kosowski, Naik, and Teo (2007) apply the seven-factor model of Fung and Hsieh (2004b) and the cross-sectional bootstrap method of Kosowski, Timmermann, Wermers, and White (2006) to examine the alphas of individual hedge funds. They conclude that hedge fund managers are able to deliver significant alphas even after being controlled for non-linear factors, and that top hedge funds' performance cannot be explained by luck.

Another strand of research examines the persistence of hedge fund performance. Using annual data, Brown, Goetzmann, and Ibbotson (1999) find no evidence of performance persistence at the annual level. Using monthly data, Agarwal and Naik (2000b) examine whether persistence is sensitive to the length of return measurement intervals by using quarterly, half-yearly and yearly returns. They find maximum persistence at the quarterly horizon. Edwards and Caglayan (2001) examine the alpha of a six-factor model, and find evidence of significant persistence among both winners and losers over one- and two-year horizons. To the contrary, Capocci and Hübner (2004) find limited evidence of persistence for middle decile funds, but not for extreme performers. Malkiel and Saha (2005) find that the probability of repeated winners is 50% at the annual horizon. Using the seven-factor model of Fung and Hsieh (2004b), Kosowski, Naik, and Teo (2007) also find that hedge fund performance persists at the annual horizon.

While most of the early studies confirm the ability of hedge fund managers to deliver significant positive alphas over the sample period from the mid 1990s to the early 2000s, recent empirical evidence points to a declining trend of alphas produced by hedge funds. Using funds-of-funds (FoFs) data from a combination of CISDM, HFR, and TASS, Fung, Hsieh, Naik, and Ramadorai (2008) find that average FoFs only delivered alpha during the period from October 1998 to March 2000. Furthermore, although an examination of the cross-section of FoFs indicates the ability of some FoFs to deliver persistent positive alphas, these once successful FoFs have recently experienced a dramatic decline in risk-adjusted performance. Using the average returns of eight broadly defined hedge fund strategies, Naik, Ramadorai, and Stromqvist (2007) also find that the mean-level of hedge fund alphas has declined substantially over the period from 1995 to 2004.

2.4 Relationship between Fund Characteristics and Fund Performance

Many studies have attempted to link a variety of fund characteristics to the cross-section of hedge fund performance. For instance, for the sample period of 1994-1996, Liang (1999) finds that hedge fund returns are related to a number of fund characteristics in a cross-sectional regression of 385 funds from HFR. First, hedge fund returns are positively related to incentive fees, suggesting better alignment of interests between fund managers and investors. Second, hedge fund returns are also positively related to fund assets, indicating the economy of scale of hedge fund operations. Third, fund returns and lock-up periods are positively correlated. Liang argues that the protection of a lock-up period allows managers to focus on relatively long-horizon investments. Last, fund returns are negatively related to fund age. One possible explanation provided by Liang is that young fund managers work harder than managers of old funds in order to build their reputation.

Looking at the sample period from 1988 to 1995 and using a combined data from MAR and HFR, Ackermann, McEnally, and Ravenscraft (1999) link fund characteristics to the Sharpe ratios of hedge funds. They show that incentive fees are positively related to Sharpe ratios, and their impact is both statistically and economically significant. They also find weak evidence that management fees reduce the Sharpe ratios of hedge funds, and that U.S. funds out-perform offshore funds.

Using data from MAR for the sample period from 1990 to 1998, Edwards and Caglayan (2001) examine the relation between the alphas of a six-factor model and fund characteristics. They find that hedge funds that pay managers higher incentive fees have higher alphas. They also find that hedge fund alpha increases at a declining rate as fund size increases. In addition, fund age appears to have significant and positive explanatory power for the alphas of some strategies, while management fees generally have a negative, but statistically insignificant, relation with alphas.

Aragon (2007) finds a positive and concave relation between hedge fund alphas and share restrictions such as look-up periods and redemption notice periods. Also discovering a positive relation between share restrictions and illiquidity in fund assets, he argues that hedge fund managers under the protection of share restriction are able to capitalize on the liquidity premium of the illiquidity fund assets that they invest in.

Agarwal, Daniel, and Naik (2007) examine the roles of managerial incentives and managerial discretion in determining hedge fund performance. Using both returns and alphas of the seven-factor model of Fung and Hsieh (2004b), they find that hedge funds with greater managerial incentives, proxied by the delta of option-like incentive fee contracts, managerial ownership, and high-water mark provisions, are associated with superior performance. They also find that funds with a higher degree of managerial discretion, proxied by longer lock-up periods and redemption notice periods, deliver superior performance.

It is worth mentioning that a critical issue that is not resolved in the extant literature is the causality of the relation between fund characteristics and fund performance. For example, a positive relation between fund size and performance may arise if large funds are able to realize economies of scale, but it may also be due to the fact that successful funds attract more money. To resolve these issues, it is important to distinguish the relation between past fund size (or fund flow) with a fund's future performance from the relation between past performance and future fund size (or fund flow). We will address these issues later in our empirical analysis.

Chapter 3

Data

3.1 Background

Information on hedge funds was not readily available to the general public until the mid-1990s. Since then, however, many commercial databases of hedge funds have become available for both industry analysis and academic research. The three best-known hedge fund databases (having more than ten years of actual data collection experience) are the Center for International Securities and Derivatives Markets (CISDM), Hedge Fund Research (HFR), and Lipper TASS (TASS). Some other notable new entrants are Morgan Stanley Capital International (MSCI), Eureka Hedge (EUR), and Standard and Poor's (S&P).[1] While there is some on-going projects to construct a comprehensive hedge fund database, most studies in the extant literature use either one or a combination of several databases from the above-mentioned list.

[1] Due to their late entry, their historical data has been produced largely through reconstructed history rather than real-time collection.

3.2 Sample Selection

We use hedge fund data from the CISDM Database (formerly known as the MAR Database).[2] It was one of the first hedge fund databases, and it began tracking Commodity Trading Advisers (CTA) in 1979 and hedge funds in 1992. The database currently tracks quantitative and qualitative information for over 4,500 existing hedge funds, funds-of-funds, and CTAs.[3] It also includes another 4,000 funds that have stopped reporting (defunct funds). We start with a sample of more than 8,000 funds. Several filters are imposed to obtain our final sample: (1) Only funds with both return and assets under management (AUM) data are included; (2) we exclude funds that only report quarterly or annually; (3) we drop funds with evident irregularity in their return or AUM time-series; (4) for the data used in the regression analysis, we further require that each fund has at least 24 months of consecutive observations. This leaves us a total of about six thousand funds (both live and defunct) in the sample period from January 1994 to December 2005. To ensure the compatibility of AUM among different funds, we convert each fund's AUM into U.S. dollars using the monthly exchange rates obtained from the U.S. Federal Reserve Board.

In order to study the time variation of the hedge fund alphas, we divide the sample into four evenly-spaced sub-periods: 1994-1996, 1997-1999, 2000-2002, and 2003-2005.[4] When conducting our analysis related to hedge fund strategies, we

[2]According to the Venn diagram of hedge funds databases reported in Agarwal, Daniel, and Naik (2007), CISDM represents 40% of the total funds covered by the four major hedge funds databases (CISDM, HFR, MSCI, and TASS). HFR, MSCI, and TASS represent 35%, 20%, and 39% of the total funds respectively. There is no report of any systematic bias in the coverage of CISDM compared to other hedge fund databases.

[3]The data provided by CISDM include time-series data of monthly returns, Net Asset Value (NAV), and AUM of each fund, and cross-sectional data of each fund's investment strategy, leverage, minimum initial investment, fee structure, and so forth.

[4]Among the robustness checks in Chapter 7, we also consider alternative sub-sample periods.

follow the classification criteria in Agarwal, Daniel, and Naik (2007), and divide the hedge funds into the following nine categories: Security Selection, Relative Value, Managed Futures, Multi-process, Directional Trading, Emerging Markets, Macro, Funds-of-Funds, and Others (unspecified).

3.3 Controls for Biases

One concern of any hedge fund study is the bias that may exist in hedge fund databases.[5] Since hedge funds are not required to report to any data agency, the first bias that hedge fund databases can suffer is selection bias. Yet, due to the two opposite effects of voluntary reporting, the direction or magnitude of selection bias is uncertain. On one hand, hedge funds are not allowed to advertise, and one of the main reasons that hedge fund managers report their information to data agencies is to gain access to investors. Therefore, it is possible that those funds with superior performance would choose voluntary reporting, while those not-so-successful funds would opt out of reporting. On the other hand, it is also possible that some successful funds that are closed to new investors would choose not to be included in any databases. Since we cannot observe those funds that are not part of any databases, the net result of these two opposite effects of self selection is unclear. According to Fung and Hsieh (2000), this bias is likely to be negligible. As such, we do not expect it to have any bearing on our main findings.

The second bias for hedge fund databases is survivorship bias. Survivorship bias arises if the database only contains information on surviving funds. While there are many reasons that a fund may stop reporting to a database, Liang (1999) finds that poor performance is the primary reason that a fund drops out of a database. Since

[5] See Fung and Hsieh (2000) and Liang (2000) for detailed discussion of various biases in hedge fund databases.

hedge funds have much higher attrition rates than mutual funds, the potential survival bias is a major concern for hedge fund research.[6] Fung and Hsieh (2000) estimate the survivorship bias to be about 3.6% per year for 1989-1997. Similarly, Brown, Goetzmann, and Ibbotson (1999) find a survivorship bias of about 3% per year for offshore hedge funds for the sample period of 1989-1995. Liang (2000) compares the HFR and MAR databases and finds an annual survivorship of 2.24%.

The third bias for hedge fund databases is incubation bias (also known as backfill or instant history bias). This bias results from the fact that some hedge funds enter the database after building up an initial, superior track-record. Since many hedge funds backfill their historical data when they enter the database, this can lead to an upward bias of the reported returns. Fung and Hsieh (2000) estimate the incubation bias to be about 1.4% per year for the TASS database during the sample period of 1994-1998.

In order to control for the well-known hedge fund biases and other issues related to hedge fund data, we adopt the following procedures throughout the paper: First, to mitigate the survivorship bias, we include both live and defunct funds in our analysis. Second, we only use data from the post-1994 period because most hedge funds databases (including CISDM) started reporting the information of defunct funds after 1994. Third, to address the concern that the reported returns of smaller funds might be biased, and that smaller funds have less investment value to institutional investors, we also examine a sub-sample that excludes funds with AUM of less than $10 million. Fourth, to consider the possible double-counting issue of including funds-of-funds in our analysis, we divide the sample into two sub-samples, funds-of-funds and funds that are not funds-of-funds. Finally, to control

[6]For example, Brown, Goetzmann, and Ibbotson (1999) document an annual attribution rate of 20% for CTAs, and 14% for offshore hedge funds.

for the incubation bias, we delete the first twelve months of each hedge fund's time-series data and repeat our analysis.[7]

3.4 Summary Statistics

Table 3.1 presents the summary statistics of the data. The total number of live funds increases from 1,520 at the end of 1994 to 3,754 at the end of 2005, while the total AUM of all funds increases from \$74 billion to \$600 billion. The dramatic increase in the total number of funds and the total assets under management is evident. We plot the total number of funds and the total AUM for every year in Figure 3.1. The plot reveals that the growth rate of total AUM outpaced that of the total number of funds in the last few years. As a result, the size of individual funds shows a steep increase in the last three years of our sample (as illustrated in Figure 3.2). The dramatic increases in both the size of individual funds and the size of the entire industry suggest that any analysis involving capacity constraints should consider two possible sources of constraints: constraints at the individual fund level and constraints at the aggregate level.

To examine the evolution of hedge fund performance, we plot the cross-section statistics (different percentiles) of monthly individual fund returns in Figure 3.3. While the average return across all funds does not seem to follow any trend, the difference between upper percentiles (good funds) and lower percentiles (bad funds) exhibits some interesting patterns. The difference between the good and bad performers was stable in the mid-1990s, but then, after a sudden increase around 1998, it began to experience a long period of decrease. These results are robust regardless of whether we examine the difference between the 95th and 5th percentiles,

[7] The results after controlling for incubation bias are provided in Chapter 7.

the 90th and 10th percentiles, or the 75th and 25th percentiles. One implication of such a finding is that the distribution of hedge fund returns does change over time, and funds in the two tails of the cross-section may experience different changes. Thus, understanding why the average level of alpha decreases over time requires a careful examination of the entire distribution of alphas.

Table 3.1: Summary Statistics of Hedge Fund Data

Cross-sectional summary statistics of the number of hedge funds, assets under management (AUM), and return (net of fees) for each year. The Number of Hedge Funds is the total number of funds that exist in the database at the end of each year. The Total AUM is the sum of the AUM of all funds at the end of each year. The Mean (Median) AUM is the cross-sectional mean (median) of individual funds' AUM at the end of each year. The Mean (Median) Return is the cross-sectional mean (median) of individual funds' average monthly returns in a given year. The Standard Deviation of Return is the cross-sectional standard deviation of individual funds' average monthly returns in a given year. The sample period extends from January 1994 through December 2005.

Year	Number of Hedge funds	Total AUM ($ billion)	Mean AUM ($ million)	Median AUM ($ million)	Mean Return (% per month)	Median Return (% per month)	S.D. of Return (% per month)
1994	1520	73.87	48.60	8.95	0.18	0.10	1.93
1995	1839	78.88	42.89	8.42	1.37	1.17	2.31
1996	2215	119.44	53.92	9.57	1.37	1.25	2.40
1997	2496	168.67	67.58	12.58	1.37	1.21	2.18
1998	2598	179.21	68.98	14.52	0.58	0.62	2.85
1999	2691	201.90	75.03	17.00	1.74	1.11	3.39
2000	2774	215.96	77.85	19.32	0.76	0.86	2.76
2001	2873	242.45	84.39	22.90	0.42	0.50	2.45
2002	3090	271.26	87.79	24.74	0.28	0.29	1.93
2003	3212	405.63	126.29	33.60	1.29	0.98	1.77
2004	3348	579.51	173.09	41.68	0.69	0.60	1.43
2005	3754	639.89	170.46	44.50	0.69	0.56	1.29

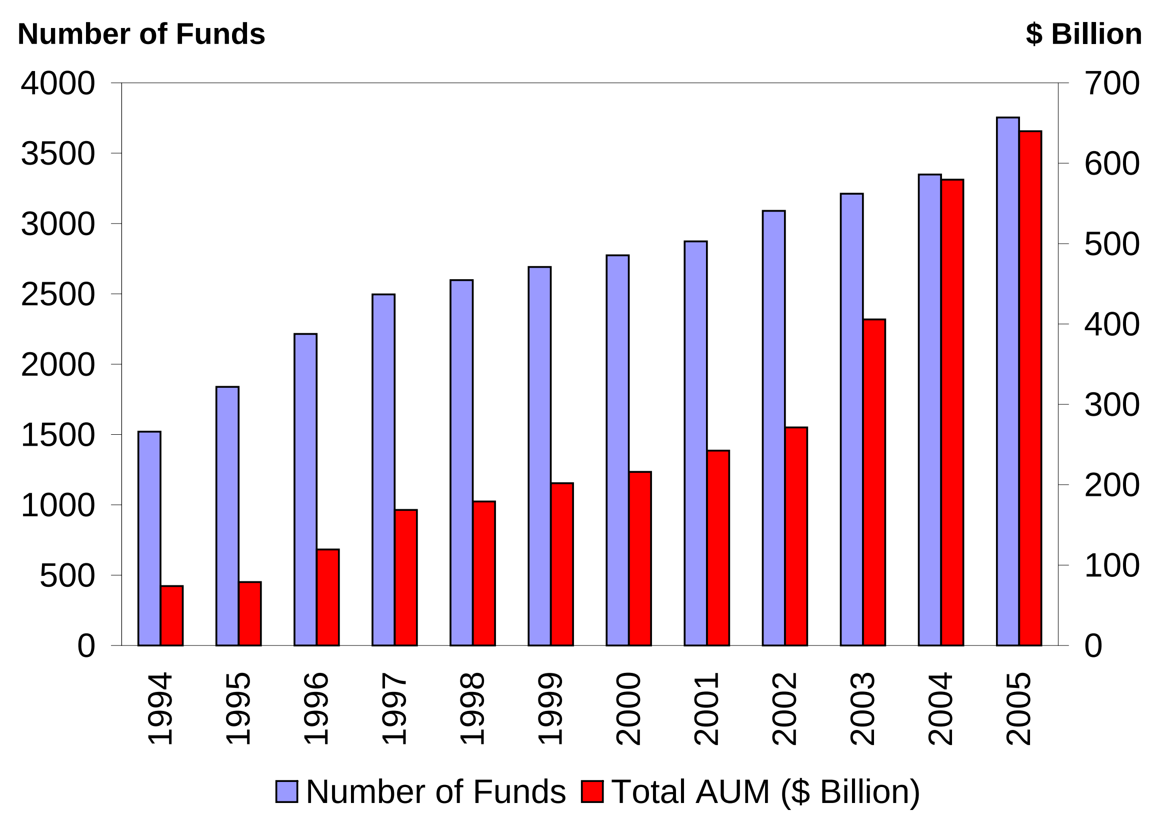

Figure 3.1: Number of hedge funds and total assets under management. The sample period extends from January 1994 through December 2005.

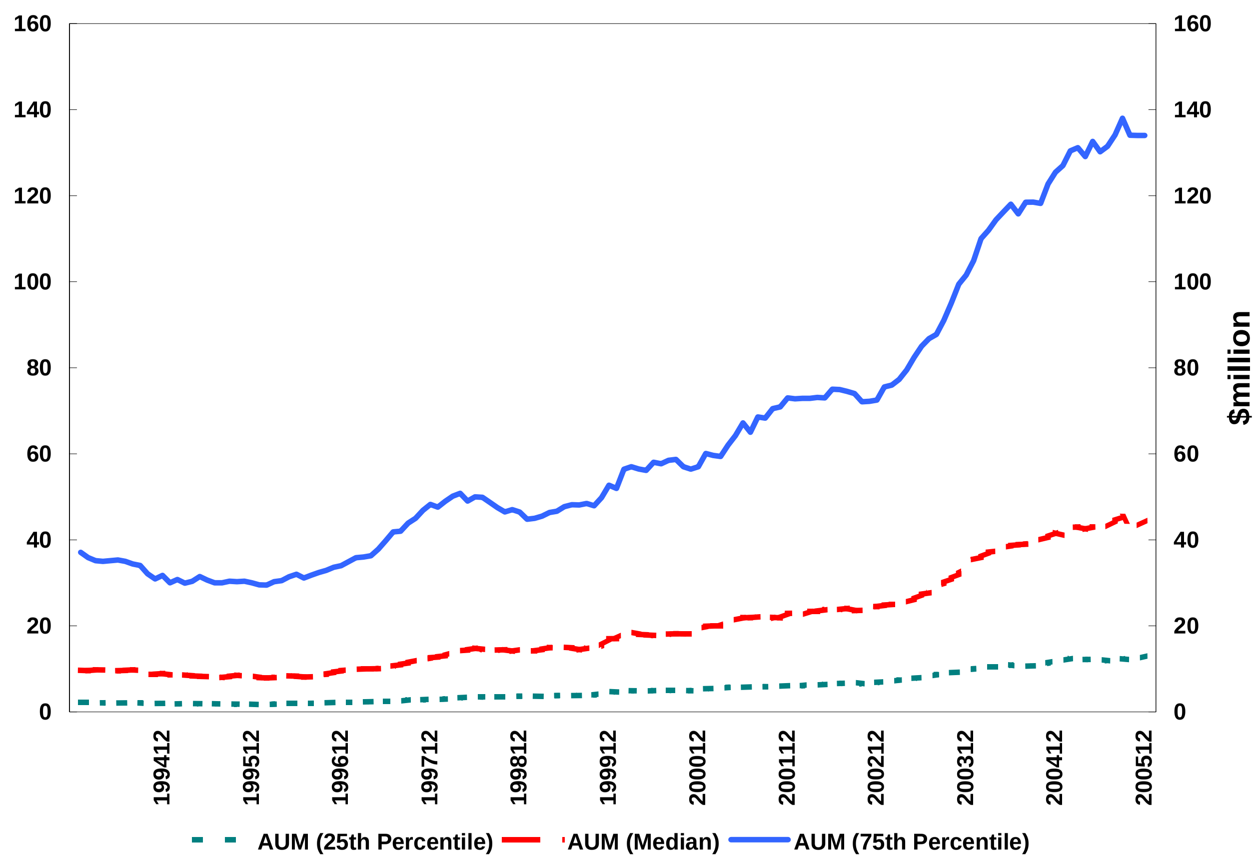

Figure 3.2: Average fund size. The 25th, 50th, and 75th percentiles of individual funds' assets under management (AUM) in each month. The sample period extends from January 1994 through December 2005.

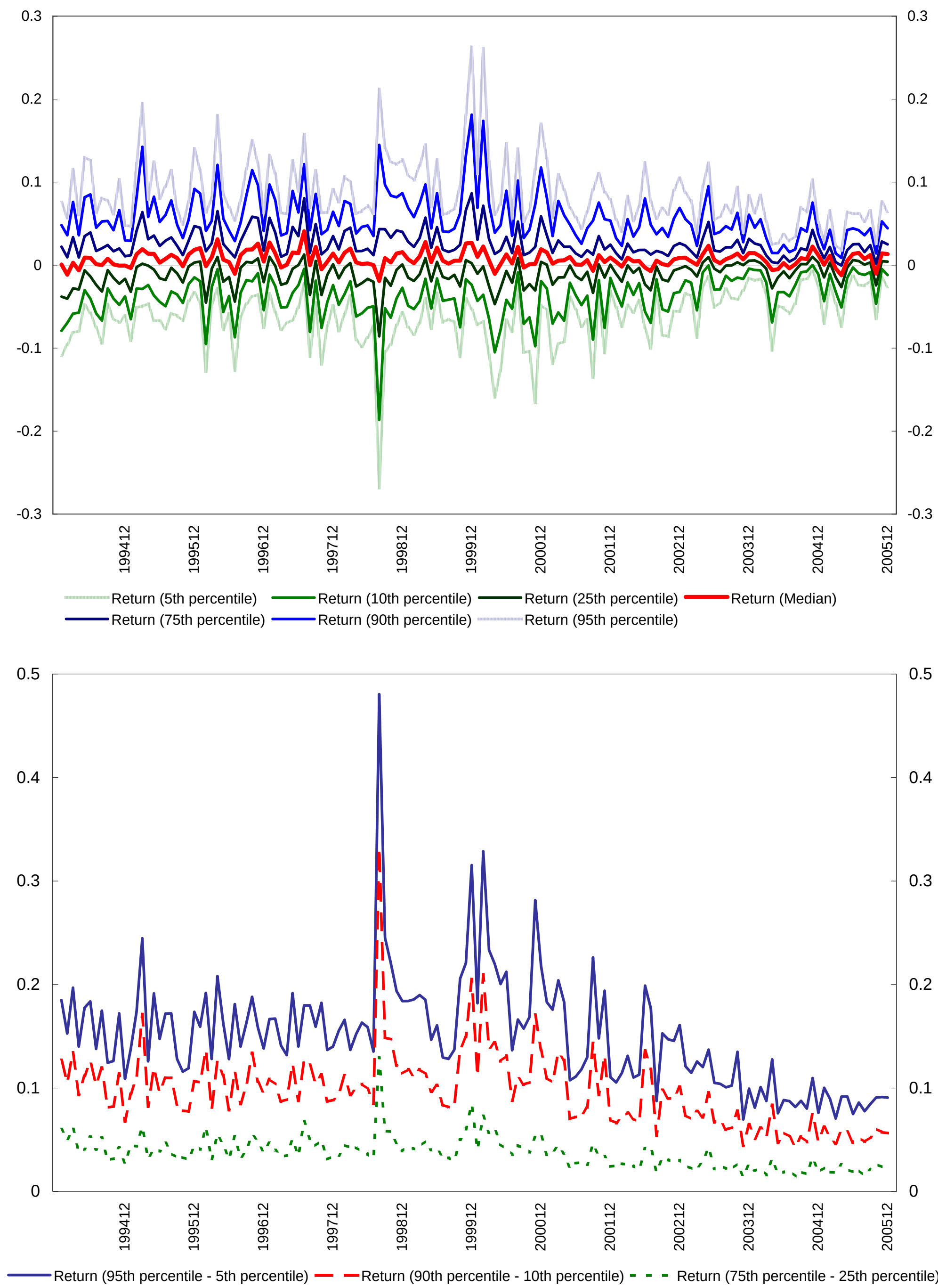

Figure 3.3: Evolution of hedge fund returns. The upper panel displays the 5th, 10th, 25th, 50th, 75th, 90th, 95th percentiles of individual hedge fund returns in each month. The lower panel displays the difference between "Top" and "Bottom" funds (95th percentile minus 5th percentile; 90th percentile minus 10th percentile; 75th percentile minus 25th percentile). The sample period extends from January 1994 through December 2005.

Chapter 4

Research Methodology

4.1 Estimation of Hedge Fund Alpha

To obtain estimates of the risk-adjusted performance (alpha) of individual hedge funds, we regress the net-of-fee monthly excess return (in excess of the risk-free rate) of each hedge fund on the seven factors constructed by Fung and Hsieh (2004). Previous studies show that hedge fund returns can be captured by a combination of conventional asset class returns and option-based strategy returns [for example, Fung and Hsieh (2001), Mitchell and Pulvino (2001), Fung and Hsieh (2002b), Agarwal and Naik (2004), Fung and Hsieh (2004a)]. Fung and Hsieh (2004b) summarize these results and find that a large portion of hedge fund returns can be explained by the returns of four traditional buy-and-hold strategies and three primitive trend-following strategies (PTFS) constructed from option prices. These factors include the Standard and Poor's (S&P) 500 return minus risk-free rate (SNPMRF), Wilshire small cap return minus large cap return (SCMLC), change in the 10-year treasury constant maturity yield (BD10RET), change in the Moody's Baa yield less 10-year treasury constant maturity yield (BAAMTSY), the return of bond primitive trend-following strategy (PTFSBD), the return of currency primitive trend-following strategy (PTFSFX), and the return of commodity primitive trend-following strategy (PTFSCOM).[1]

The intercept α^i in the regression below represents the risk-adjusted performance of fund i. We estimate the following seven-factor model, and obtain estimates of α^i:

$$\begin{aligned} r_t^i = \alpha^i &+ \beta_1^i SNPMRF_t + \beta_2^i SCMLC_t + \beta_3^i BD10RET_t + \beta_4^i BAAMTSY_t \\ &+ \beta_5^i PTFSBD_t + \beta_6^i PTFSFX_t + \beta_7^i PTFSCOM_t + e_t^i, \end{aligned} \tag{4.1}$$

where r_t^i is the net-of-fee excess return of fund i in month t; α^i is the alpha of hedge fund i over the regression time period; $\beta_1^i, \ldots, \beta_7^i$ are the factor loadings of fund i.

4.2 Kernel Density Estimation

Since we are interested in the distribution of alphas, we estimate the empirical probability density function using individual hedge fund alphas. The density estimates are obtained by adapting the kernel density estimator introduced by Rosenblatt (1956) and Parzen (1962), with sample weight attached to each observation. The kernel density estimate $\hat{f}_h$ of a univariate density f based on a sample $Y_1, \ldots, Y_n$ of size n, with weights $\theta_1, \ldots, \theta_n \big(\sum_j \theta_j = 1 \big)$, is:

$$\hat{f}_h(y) = \sum_{j=1}^{n} \frac{\theta_j}{h} K\left(\frac{y - Y_j}{h} \right), \tag{4.2}$$

[1]The seven-factor model has been used in recent studies including Kosowski, Naik, and Teo (2007); Agarwal, Daniel, and Naik (2007); Fung, Hsieh, Naik, and Ramadorai (2008); and Naik, Ramadorai, and Stromqvist (2007).

where h is the bandwidth, and $K(\cdot)$ is the kernel function. The critical issue in kernel density estimation is the choice of bandwidth; we use the Sheather and Jones (1991) plug-in method to select the bandwidth. We use the Gaussian kernel function and equal weighting ($\theta_j = 1/n,\ j = 1, \ldots, n$) to estimate the actual empirical density.

4.3 Quantile Regression

Extant studies have shown that the mean level of return or alpha are correlated with certain fund characteristics. For example, Liang (1999) finds that fund return is positively related to the incentive fee, fund size, and lockup period, and negatively related to fund age. Aragon (2007) documents that the lockup requirement, minimum investment, and redemption notice period can explain a significant portion of hedge fund alpha. Yet, all of the aforementioned studies use the ordinary least square (OLS) estimation method. OLS regression only captures the effects of independent variables on the conditional mean of the dependent variable. In the event that an independent variable has different (or even opposite) effects on the tails of distribution of the dependent variable, then quantile regression is a better-suited methodology.

Quantile regression [introduced by Koenker and Bassett (1978)] extends OLS regression from the conditional mean to conditional quantiles of the dependent variable. It is particularly useful when regression coefficients depend on the quantile. (See Appendix A for details about the estimation method of quantile regression.) We use individual hedge fund alpha as the dependent variable and examine the effects of various fund characteristics on different quantiles of alpha. When computing confidence intervals for the parameter estimates, we use the resampling method of He and Hu (2002), which is robust even when errors in the linear model are correlated.

4.4 Counter-factual Density Analysis

While quantile regression is useful in explaining the impact of fund characteristics on different quantiles of the hedge fund alpha in a given period, it cannot explain why the distribution of alpha changes from one period to another. Any change in the distribution over time consists of two components: (1) "change in characteristics effect"(e.g., the change in fund size, compensation structure, etc.), and (2) "change in market conditions effect" (e.g., the change in the relation between fund characteristics and alpha).

To separate the contributions of these two effects, we adapt the counter-factual density method, an econometric method that has been used in labor economics, for example, in studying changes in income distribution. For the purpose of illustration, we compare the distribution of alpha between the first period (1994-1996) and the most recent period (2003-2005). We follow the semi-parametric method in DiNarodo, Fortin, and Lemieux (1996) and construct the counter-factual density of the hedge fund alphas for the most recent period, assuming that fund characteristics have remained unchanged since the first period.[2] The difference between the actual density of the last period and the counter-factual density captures the change in characteristics effect, while the difference between the counter-factual density and the actual density of the first period captures the change in market conditions effect.

[2]This method is essentially a weighted kernel density using a probit model to calculate the reweighting scheme. See Appendix B for details about the construction of counter-factual density.

4.5 Regression Analysis of Fund Flow on Alpha

To develop a better understanding of the dynamic relation between flow and alpha, we first examine whether investors chase alpha, (i.e., whether funds with positive alphas attract more flows than funds without positive alphas).

We use individual fund data and follow the methodology in Fung, Hsieh, Naik, and Ramadorai (2008) to test the relation between the two variables of interest: fund flow and past performance. The flow that goes into a fund is defined as:

$$Flow_t^i = \frac{AUM_t^i - AUM_{t-1}^i(1 + R_t^i)}{AUM_{t-1}^i}, \tag{4.3}$$

where $Flow_t^i$ is the flow for fund i in month t; AUM_t^i is the assets under management (AUM) of fund i at the end of month t; and R_t^i is the return for fund i in month t.

To measure past performance, we adopt a rolling-window method to estimate alpha for each fund. For each observation of monthly fund flow, we use the seven-factor model and the previous n months of data to estimate the fund's alpha (e.g., n = 24 months). To test whether funds with higher alpha have larger future flow, we first sort funds into quintiles (five groups) by the ranking of each fund's alpha in the past n months. We then estimate the following regression model separately for funds in each group using Fama-Macbeth approach:

$$Flow_t^i = \gamma_0 + \gamma_1 PerfRank_{t-1,t-n}^i + \gamma_2 Flow_{t-1}^i + u_t^i, \tag{4.4}$$

where $Flow_t^i$ is the flow for fund i in month t; $PerfRank_{t-1,t-n}^i$ is the relative performance ranking of a fund (which takes values between 0 and 1 in ascending order) within its quintile group; and $Flow_{t-1}^i$ is the lagged flow for fund i in month

$t-1$.

The intercept of a group's regression represents the baseline flow for that group (i.e., measuring flows related to performance ranking among groups). On the other hand, the coefficient γ_1 of each group can be interpreted as the sensitivity of flow on past performance within that group (i.e., measuring flows related to performance ranking within each group).

To attenuate the effects of outliners, we eliminate those observations with monthly flow of larger (smaller) than 50% (-50%). We implement the Fama and MacBeth (1973) methodology to control for possible cross-sectional correlation. When calculating the t-statistics of the time-series average of the cross-sectional regression coefficients, we use Newey and West (1987) standard errors (with 24 lags) to control for possible autocorrelation.

4.6 Regression Analysis of Alpha on Fund Flow and Strategy Flow

As discussed earlier, capacity constraints can arise from two sources: (1) the unscalability of managers' abilities, and (2) the constraint of limited profitable opportunities in the market. To disentangle these two hypotheses, we use three variables: alpha, past fund flow, and past strategy flow. If the unscalability of managers' abilities is the source of constraints, fund flow should have a negative impact on a fund's future performance. If the limitation of profitable opportunities is the cause of constraints, strategy flow should have a negative impact on funds' future performance. If both fund-level and strategy-level capacity constraints exist, we should find a combination of these two effects after including both fund flow and strategy flow in a regression analysis.

The fund-level flow is calculated as in equation 3, while the strategy-level flow is calculated as the following:

$$Flow_{st} = \sum_{i=1}^{Ns} \left(AUM_t^i - AUM_{t-1}^i (1 + R_t^i) \right) \Big/ \sum_{i=1}^{Ns} AUM_{t-1}^i, \tag{4.5}$$

where $Flow_{st}$ is the flow into strategy s in month t; Ns is the total number of funds in strategy s in month t; AUM_t^i is the AUM of fund i at the end of month t; R_t^i is the return for fund i in month t; and s refers to each of the nine strategies defined in Chapter 2.

We follow the method in Naik, Ramadorai, and Stromqvist (2007), and construct a measure of risk-adjusted return using a rolling-window out-of-sample method. For each month, we calculate a fund's factor loadings $(\hat{\beta}_1^i, \ldots, \hat{\beta}_7^i)$ of the seven factors using the previous n months of data (n = 24 months).[3] We then calculate the risk-adjusted return as:

$$\begin{aligned} Adj\_Ret_t^i = r_t^i - (&\hat{\beta}_1^i SNPMRF_t + \hat{\beta}_2^i SCMLC_t + \hat{\beta}_3^i BD10RET_t + \hat{\beta}_4^i BAAMTSY_t \\ &+ \hat{\beta}_5^i PTFSBD_t + \hat{\beta}_6^i PTFSFX_t + \hat{\beta}_7^i PTFSCOM_t) \end{aligned} \tag{4.6}$$

where $Adj\_Ret_t^i$ is the risk-adjusted excess return of fund i in month t; r_t^i is the net-of-fee excess return of fund i in month t; and $\hat{\beta}_1^i, \ldots, \hat{\beta}_7^i$ are the factor loadings of fund i calculated using the previous n months of data.

To disentangle fund-level and strategy-level capacity constraints, we compare the explanatory power of the lagged fund-level and lagged strategy-level variables

[3] we also consider the cases of n = 12 months or n = 36 months as robustness checks in Chapter 7.

in predicting future risk-adjusted returns:

$$Adj\_Ret^i_t = f\big(\text{Lagged Fund-level Variables},\ \text{Lagged Strategy-level Variables}\big), \tag{4.7}$$

where the fund-level variables include fund flow, an interaction term of fund flow and the indicator variable of whether a fund is larger than the size of the median fund in its strategy, fund size, and squared fund size.[4] The strategy-level variables include strategy flow, strategy size, and the total number of funds in a strategy. We use the panel data approach to estimate equation 4.7. For coefficient estimates, we compute the t-statistics based on Rogers (1993) standard errors that control for the cross-sectional correlation of returns across funds.

Finally, to examine whether funds with certain characteristics are more or less subject to capacity constraints, we implement a two-step estimation procedure. In the first step, we estimate each fund's alpha-flow sensitivity by running a time-series regression of risk-adjusted return on fund i on lagged fund-level flow and lagged strategy-level flow:

$$Adj\_Ret^i_t = \lambda^i_0 + \lambda^i_1 Flow^i_{t-1} + \lambda^i_2 Flow_{st-1} + \eta^i_t. \tag{4.8}$$

In the second step, we take the coefficient estimates from the previous step and run a cross-sectional regression of $\hat{\lambda}^i_1$ on various fund characteristics. The specification is:

$$Alpha\_Flow\_Sensitivity^i = f\big(\text{Fund Characteristics}^i\big), \tag{4.9}$$

where the fund characteristics variables include fund size, incentive fee, manage-

[4]The squared fund size is included to control for the nonlinear effects that have been documented by Getmansky (2005).

ment fee, an indicator variable for whether a fund has a lockup period, redemption notice period, an indicator variable for whether a fund uses leverage, and dummy variables for the nine strategies. Standard OLS regression is used to estimate the cross-sectional regression, and White (1980) standard errors are used to compute t-statistics to control for heteroskedasticity.

Chapter 5

Empirical Results

5.1 Empirical Distribution of Individual Hedge Fund Alpha: Hedge Fund Bubble Hypothesis versus Capacity Constraint Hypothesis

Motivated by the recent studies of Fung, Hsieh, Naik, and Ramadorai (2008) and Naik, Ramadorai, and Stromqvist (2007), the first contribution of this thesis is to explain why hedge fund alpha has decreased over time. While previous studies have examined the average hedge fund performance, they have been unable to differentiate between two alternative causes of the decrease in alpha in the hedge fund industry; namely, an increase in the proportion of unskilled managers who produce negative alpha, and a decrease in the percentage of "star" funds that deliver positive alphas. In this section, we will examine the performance of individual hedge funds to determine if the average hedge fund alpha has decreased due to more unskilled managers (which will lead to the expansion of the left tail of the distribution), or to fewer successful managers (which will lead to the shrinkage of the right tail of the distribution).

We first use the seven-factor model to explain the cross-sectional average of hedge fund returns, and present the estimation results for the full sample (1994-2005). Table 5.1 reports the summary statistics of the seven factors. Table 5.2 provides the coefficient estimates and t-statistics using the average monthly return of (1) all funds, (2) funds with AUM of more than $10 million, (3) funds that exclude funds-of-funds[1], and (4) funds-of-funds as the dependent variable. To compare these results with the published indexes by CISDM, we use the return of the CISDM Equally-weighted Hedge Fund Index or the CISDM Fund-of-funds Index as the dependent variable. In all cases, the seven-factor model explains a significant portion of the average hedge fund returns with adjusted R-squares ranging from 55% to 75%. The alpha (the intercept of the regression) is positive, ranging from 0.21 to 0.51 percent per month, and statistically significant in all cases. When we divide the sample into four sub-samples (1994-1996, 1997-1999, 2000-2002, 2003-2005), we find that the alpha of each of the four average hedge fund returns shows a downward trend over the last decade. The alphas are positive and significant during the first three sub-periods; however, none of the three is significant in the last period (see Table 5.3). Our results successfully replicate all of the stylized facts that have been documented in the previous literature.

To understand what leads to the decrease in overall alpha, we analyze the distribution of individual fund alpha. Table 5.4 reports the sample average of the alphas of individual funds. The average of individual fund alphas in each sub-period resembles the alpha of the average return. For example, for the sample of all funds, the average alphas are 0.49, 0.47, 0.37, and 0.07 percent per month during 1994-1996, 1997-1999, 2000-2002, and 2003-2005 respectively, while the alphas of

[1]We exclude funds of funds from consideration to avoid double-counting.

the average returns are 0.54, 0.40, 0.39, and 0.13 percent per month for the same periods (see Table 5.4). Again, the result shows that alpha decreases over time. The average of individual alphas in the last period is much lower than those in the earlier periods.

Panel A of Table 5.5 presents percentiles of the alpha distribution in four sub-periods. We find that the upper percentiles of the distribution have decreased substantially from the first period to the last period. In contrast, the lower percentiles of the distribution have not shown any significant changes. For example, the change in the 95th percentile is -1.33% (from 3.03% during 1994-1996 to 1.70% during 2003-2005), and the change in the 5th percentile is only -0.10% (from -1.59% during 1994-1996 to -1.70% during 2003-2005). To ensure that our results are robust, we repeat our analysis for funds with AUM of more than $10 million, for funds that exclude funds-of-funds, and for funds-of-funds only. Irrespective of which sample we use, the pattern of changes in upper and lower percentiles is similar.

Examining the empirical density of alpha confirms our findings. Figure 5.1 shows the evolution of the empirical densities over four sub-periods. By comparing the density of the first two sub-periods (1994-1996 versus 1997-1999), we see that the two densities are very similar. However, the density of the third sub-period (2000-2002) is different from those of the first two sub-periods. This change in the distribution of alpha becomes much more pronounced in the last sub-period (2003-2005). Figure 5.2 plots empirical densities of alpha for the first and last sub-periods (1994-1996 versus 2003-2005). It shows that while the left tail of the distribution has remained unchanged, the right tail of the distribution shifted to the center in the last sub-period. Plotting the difference between the two densities reveals an even clearer picture—compared to the mid-1990s, there is a much smaller portion of funds with large positive alpha in the early 2000s (see Figure 5.2).

We conclude that the change in the distribution of alpha is due to a decrease in the proportion of funds with large positive alpha. Our evidence is consistent with the prediction of the capacity constraint hypothesis, which states that the right tail of the distribution should shrink over time. We find no evidence of an increasing percentage of funds with large negative alpha. Thus, we do not find supporting evidence for the hedge fund bubble hypothesis, which predicts that the left tail of distribution should expand over time. Finally, we compare the empirical densities of the first and last sub-periods for three sub-samples (funds with AUM of more than $10 million, funds that exclude funds-of-funds, and funds-of-funds only), and find that our conclusion remains the same (see Figure 5.3-5.5).

5.2 Effects of Fund Characteristics on the Distribution of Alpha

To examine whether fund characteristics have different (or even opposite) impacts on the two tails of the alpha distribution, we use individual fund alpha as a dependent variable and run quantile regressions of alpha on various characteristic variables.

Table 5.6 reports the estimates of the quantile regression. Consistent with the findings in the previous literature, which relies on the ordinary least square (OLS) regression, we find that the coefficients of incentive fee, the provision of high water mark, and the redemption period are significant in each quantile (with a few exceptions). Furthermore, the magnitude of coefficient estimates of each variable is similar across all quantiles, implying that each variable has a similar impact on alphas in different quantiles.

Quantile regression analysis reveals several results that could not be uncovered by OLS regression. For example, although fund size is positively related to the median of alpha (as documented in previous literature), it has opposite effects on the upper and lower quantiles of alpha (e.g., good and bad funds). The coefficient estimates of fund size are negative and significant for the top 10% and top 5% quantiles of alpha. Therefore, when fund size becomes larger, the performance of funds with large alpha will deteriorate. This evidence provides support for the capacity constraint hypothesis.

5.3 Decomposition of the Change in the Distribution of Alpha: Change in Characteristics versus Change in Market Conditions

How much of the change in the distribution of alpha is due to the increased competition in a more crowded hedge fund industry? After all, both the hedge fund industry and the overall financial market have changed significantly since the mid-1990s. On the other hand, how much of the disappearance of alpha producing funds is a result of individual funds growing too large? From our previous analysis, we have shown that the average hedge fund was significantly larger in 2005 than it was a decade ago. To address these questions, we want to compare funds that are similar in size and other characteristics across both time periods. In the following section, we apply the counter-factual density method to achieve this comparison.

Given the dramatic increase in the size of individual funds over time and the negative relation between fund size and the upper quantiles of alpha, it is likely that the change in fund characteristics has contributed to the shrinkage of the right tail of distribution (i.e., the change in the proportion of good funds). However, as we explain in the methodology section, any change in the distribution consists of two effects: change in characteristics effect (the change in fund size, compensation structure, etc.), and change in market conditions effect (the change in the relation between fund characteristics and alpha). Now we decompose the change in the distribution of alpha and examine these two effects.

For the purpose of illustration, we consider two sub-periods: 1994-1996 and 2003-2005. We apply the method of DiNarodo, Fortin, and Lemieux (1996) and construct the counter-factual density of alphas in the last period (2003-2005), assuming that the fund characteristics have remained unchanged since the first period (1994-1996).

As illustrated in Figure 5.6, the difference between the actual density of the 2003-2005 period and the counter-factual density (i.e., the change in composition effect) explains a substantial portion of the change of distribution from the 1994-1996 to the 2003-2005 period. In other words, the change in fund characteristics (such as the growing size of individual funds) does contribute to the shrinkage of the right tail of alpha.

The difference between the counter-factual density and the actual density of the first period (1994-1996), which captures the change in market condition effect, also contributes to the disappearance of funds with large positive alpha. This result demonstrates that another reason for the disappearance of the right tail is the change in the relation between alpha and fund characteristics (e.g., the increasing competition for the limited profitable opportunities). For funds sharing the same characteristics between the 1994-1996 and 2003-2005 periods, it is much more difficult to obtain positive alpha in the later period than in the early period.

This result suggests the existence of capacity constraint in the aggregate level. In the following sections, we will examine the relation between flow and alpha, and investigate the economic reasons for capacity constraints by comparing the effects of fund-level and strategy-level variables on the future performance of individual hedge funds.

5.4 Do Hedge Fund Investors Chase Alpha?

In this section, we will examine whether hedge fund investors are performance chasers. We use the Fama and MacBeth (1973) method to study the relation between fund flow and fund past performance. Table 5.7 presents the results of regressing fund flow on alpha of the previous period. The alpha-chasing behavior of hedge fund investors is evident. The baseline flow for each group (the intercept of the regression) monotonically increases from the group with the worst past performance (-1.82 percent monthly flow) to the group with the best past performance (1.05 percent monthly flow). There is also evidence for alpha-chasing behavior within each group. The estimate of γ_1 (the sensitivity of flow on past performance within that group) is positive and significant in all five groups, suggesting that even for funds in the same group, investors direct more funds to those that delivered a relatively better past performance. Our findings are much stronger than those reported in the previous literature [Fung, Hsieh, Naik, and Ramadorai (2008)]. We perform robustness checks by repeating the analysis in several sub-samples. The results remain the same for funds with AUM of more than $10 million, and for the sub-sample without funds-of-funds. The results in the sub-sample of funds-of-funds are somewhat weaker and consistent with the results of Fung, Hsieh, Naik, and Ramadorai (2008), who also find that there is less performance-chasing behavior within each group. Still, we find strong evidence for alpha-chasing behavior across groups, even for the funds-of-funds case. Our analysis provides evidence for the alpha-chasing behavior of hedge fund investors.

5.5 Sources of Capacity Constraints: Fund-level versus Strategy-level

Our previous results suggest that hedge fund investors are chasing past winners, while the hedge fund industry may be subject to seriously capacity constraints. A negative relationship between aggregate flow and average fund performance has been shown to exist [see Fung, Hsieh, Naik, and Ramadorai (2008) and Naik, Ramadorai, and Stromqvist (2007)]. However, is this a result of a glut of assets flowing into each strategy (competing away its available profitable opportunities), or is it due to the increased capital that individual funds have absorbed (forcing managers to resort to less profitable projects in an effort to utilize the new capital)? In the following section, we will study the linkage of fund-level and strategy-level variables with a fund's future performance to answer these questions.

To disentangle the two alternative reasons for capacity constraints (i.e., the constraint of limited profitable opportunities in the market and the unscalability of managers' abilities), we compare the impact on a fund's future performance of past fund-level flow with that of past strategy-level flow. Table 5.8 reports the results of regressing risk-adjusted returns (estimated using the rolling-window out-of-sample method) on lagged fund-level variables and strategy-level variables. We find several interesting results.

First, fund-level flow has a positive impact on a fund's future performance for smaller funds, but a negative impact for larger funds. For example, in specification 1, the coefficient of fund flow is 0.44 and the coefficient of the interaction term of fund flow and the large fund dummy is -0.63. In other words, while an increase in flow leads to better future performance for smaller funds, an increase in flow actually leads to lower future risk-adjusted returns for larger funds. This finding is consistent with the unscalability of managers' abilities hypothesis. While a fund is still small, a fund manager can absorb any new money he or she receives without sacrificing performance. However, as a fund's size becomes larger, it will become harder for the fund manager to "scale up" the profits accordingly.

Second, we find that strategy-level flow always has a negative and significant impact on a fund's future performance (the coefficient ranges from -0.95 to -1.17 in different specifications). This is consistent with the hypothesis of limited profitable opportunities. Given the limited profitable opportunities in the market, the more money that is put into funds in the same strategy, the lower the profit each fund is able to extract from the market.

Third, we find that fund flow and strategy flow have more explanatory power than size variables do. This is evident in specifications 3 and 7 in Table 5.8. When both flow and size variables are included, only flow variables remain significant. This result indicates that there may be heterogeneous abilities among fund managers (i.e., some managers can manage larger funds than others). Therefore, fund size is less useful than fund flow in predicting future performance.

Finally, we find that both fund-level variables and strategy-level variables remain significant when they are included in the same specification. Furthermore, a comparison of the economic significance of the two flow variables suggests that strategy-level flow has a more negative impact than fund-level flow does.

In summary, our findings indicate that the economic sources of capacity constraints arise from both the unscalability of managers' abilities and the limited profitable opportunities in the market.

5.6 Implications for Hedge Fund Investors: Cross-sectional Difference of Capacity Constraints

Hedge fund investors chase alpha, yet hedge funds are subject to capacity constraints. Every hedge fund investor faces the following problem: If each investor allocates investments in hedge funds based on past performance, his or her own action will attenuate the alphas of those funds that he or she invests in. To address this dilemma, we ask the question of whether it is possible to select strategies or funds that are less affected by capacity constraints.

To test whether capacity constraints vary across different strategies, we repeat the analysis performed in the previous sub-section for each strategy separately. Table 5.9 reports the panel regression results for nine strategies (specification 8 in Table 5.8). We find that the coefficients of strategy flow are negative in seven out of the nine strategies, with the exception of directional trading and emerging markets. Furthermore, the coefficients of strategy flow are statistically significant for security selection, relative values, and managed futures (along with two other strategies). These findings are intuitive—for such strategies as security selection and relative values, profit depends on either the mis-valuation of certain securities or the divergence of values of related securities. An increase in the total capital that is searching for these opportunities is likely to reduce profitability. For such strategies as directional trading and emerging markets, it is unlikely that new capital will have a significant impact on the direction of market movement. Thus, these types of strategies are less subject to capacity constraints.

Another finding from Table 5.9 is that the funds-of-funds also suffer from capacity constraints, although the magnitude of the impact of fund-level flow on funds-of-funds is smaller than that on other funds. This result indicates that while funds-of-funds managers can use the additional flexibility of managing a portfolio of individual funds to allocate new capital and to alleviate the fund-level capacity constraint, they are unable to completely eliminate the capacity constraints in the individual funds in which they invest.

Finally, to test whether certain types of funds are more or less subject to capacity constraints, we examine whether the sensitivity of alpha to fund flow (from the time-series regression of each individual fund) depends on certain fund characteristics. The results are reported in Table 5.10. We find that larger funds are more sensitive to fund flow. In addition, funds with higher management fees are more subject to capacity constraint, while funds with higher incentive fees are actually less subject to capacity constraint. Our findings indicate that there is significant cross-sectional variation in the impact of capacity constraints on funds using different strategies and on funds with different characteristics.

Table 5.1: Summary Statistics of the Seven Factors

Summary statistics of the seven factors: SNPMRF is the S&P 500 return minus risk-free rate, SCMLC is the Wilshire small cap minus large cap return, BD10RET is the change in the constant maturity yield of the 10-year Treasury, BAAMTSY is the change in the spread of Moody's Baa minus the 10-year Treasury, PTFSBD is the return of bond primitive trend following strategy, PTFSFX is the return of currency primitive trend following strategy, and PTFSCOM is the return of commodity primitive trend following strategy. The sample period extends from January 1994 through December 2005.

Factors	Mean	S.D. of	Cross-correlations						
	Return(%)	Return(%)	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM
SNPMRF	0.62	4.25	1.00						
SCMLC	0.11	3.31	−0.05	1.00					
BD10RET	−0.01	0.23	0.02	0.04	1.00				
BAAMTSY	0.00	0.12	−0.10	−0.26	−0.63	1.00			
PTFSBD	−0.19	15.67	−0.14	−0.06	−0.11	0.09	1.00		
PTFSFX	−0.28	18.98	−0.11	0.05	−0.17	0.14	0.14	1.00	
PTFSCOM	−0.86	12.73	−0.10	−0.01	−0.07	0.03	0.14	0.26	1.00

Table 5.2: Estimates of the Seven-Factor Model

Coefficients, t-statistics (in parentheses), and R-square of the seven-factor regression model in explaining the average return of hedge funds. Newey and West (1987) standard errors (three lags) are used to compute t-statistics. The dependent variables are listed on the top of each column. In the first four columns, the dependent variables are, respectively, the average monthly return of all funds, of funds with AUM of more than $10 million, of funds that exclude funds-of-funds, and of funds-of-funds. In the last two columns, we use the returns of two indexes provided by CISDM: CISDM Equally-weighted Hedge Fund Index and CISDM Fund-of-funds Index as dependent variables. The independent variables are as follows: SNPMRF is the S&P 500 return minus risk-free rate, SCMLC is the Wilshire small cap minus large cap return, BD10RET is the change in the constant maturity yield of the 10-year Treasury, BAAMTSY is the change in the spread of Moody's Baa minus the 10-year Treasury, PTFSBD is the return of bond primitive trend following strategy, PTFSFX is the return of currency primitive trend following strategy, and PTFSCOM is the return of commodity primitive trend following strategy. The sample period extends from January 1994 through December 2005.

	avg. Ret. of All Funds	avg. Ret. of Funds (AUM>10m)	avg. Ret. of Funds (not FoFs)	avg. Ret. of FoFs	CISDM E.W. H.F. Index	CISDM FoFs Index
INTERCEPT	0.46**	0.47**	0.49**	0.28**	0.51**	0.21**
	(5.66)	(5.88)	(5.91)	(2.70)	(4.71)	(2.46)
SNPMRF	0.21**	0.21**	0.21**	0.19**	0.36**	0.17**
	(9.34)	(9.16)	(9.36)	(7.45)	(13.42)	(7.29)
SCMLC	0.17**	0.19**	0.17**	0.18**	0.30**	0.15**
	(5.09)	(5.30)	(5.19)	(5.23)	(7.19)	(6.56)
BD10RET	−1.44**	−1.47**	−1.49**	−1.30**	−0.74	−1.11**
	(−3.50)	(−3.39)	(−3.50)	(−2.59)	(−1.64)	(−2.50)
BAAMTSY	−2.81**	−2.70**	−2.73**	−3.26**	−1.99*	−2.07**
	(−3.15)	(−2.76)	(−3.08)	(−2.60)	(−1.80)	(−2.39)
PTFSBD	0.01	0.00	0.01**	−0.01	−0.01	−0.02*
	(1.44)	(0.61)	(2.11)	(−1.50)	(−1.23)	(−1.85)
PTFSFX	0.02**	0.02**	0.02**	0.01*	0.00	0.01
	(6.02)	(5.10)	(6.53)	(1.67)	(1.15)	(1.44)
PTFSCOM	0.03**	0.02**	0.03**	0.01*	0.01	0.01**
	(2.47)	(2.46)	(2.52)	(1.78)	(1.40)	(2.36)
Adj. R^2	57.81%	59.40%	57.34%	55.21%	75.58%	57.55%

** and * denote significance at the 5% and 10% levels, respectively.

Table 5.3: Alpha of Average Hedge Fund Returns

Alpha (percent per month), t-statistics (in parentheses), and adjusted R-square of the seven-factor model in four sub-periods. Newey and West (1987) standard errors (three lags) are used to compute t-statistics. The dependent variables are listed on the top of each column. In the first four columns, the dependent variables are, respectively, the average monthly return of all funds, of funds with AUM of more than $10 million, of funds that exclude funds-of-funds, and of funds-of-funds. In the last two columns, the dependent variables are, respectively, the return of CISDM Equally-weighted Hedge Fund Index, and the return of CISDM Fund-of-funds Index. The independent variables are as follows: SNPMRF is the S&P 500 return minus risk-free rate; SCMLC is the Wilshire small cap return minus large cap return; BD10RET is the change in the 10-year treasury constant maturity yield; BAAMTSY is the change in the Moody's Baa yield less 10-year treasury constant maturity yield; PTFSBD is the return of bond primitive trend-following strategy; PTFSFX is the return of currency primitive trend-following strategy; and PTFSCOM is the return of commodity primitive trend-following strategy.

Sample Period	Average Return of All Funds	Average Return of Funds (AUM>10m)	Average Return of Funds (not FoFs)	Average Return of FoFs	CISDM E.W. H.F. Index	CISDM FoFs Index
	Alpha; (t); Adj. R^2	Alpha; (t); Adj. R^2	Alpha; (t); Adj. R^2	Alpha; (t); Adj. R^2	Alpha; (t); Adj. R^2	Alpha; (t); Adj. R^2
1994–1996	0.54; (2.74); 42.9%	0.52; (3.78); 44.7%	0.59; (2.69); 43.5%	0.17; (0.99); 35.9%	0.53; (3.24); 71.4%	0.10; (0.59); 50.8%
1997–1999	0.40; (1.95); 72.4%	0.47; (2.66); 73.5%	0.38; (1.83); 70.0%	0.46; (2.41); 78.9%	0.75; (3.72); 87.8%	0.27; (1.95); 74.6%
2000–2002	0.39; (2.96); 73.9%	0.44; (3.53); 77.0%	0.42; (3.00); 73.4%	0.27; (2.24); 65.5%	0.49; (3.30); 80.8%	0.21; (2.26); 64.2%
2003–2005	0.13; (0.91); 70.5%	0.12; (0.86); 68.6%	0.17; (1.07); 69.2%	0.03; (0.23); 62.4%	0.35; (2.14); 76.8%	0.06; (0.53); 59.1%

Table 5.4: Alphas of Individual Hedge Funds

Cross-sectional means of individual hedge fund alphas (percent per month). We implement the seven-factor model for each fund and then calculate the average alpha across funds. For each fund, the dependent variable in the time-series regression is net-of-fee return. The independent variables are as follows: SNPMRF is the S&P 500 return minus risk-free rate; SCMLC is the Wilshire small cap return minus large cap return; BD10RET is the change in the 10-year treasury constant maturity yield; BAAMTSY is the change in the Moody's Baa yield less 10-year treasury constant maturity yield; PTFSBD is the return of bond primitive trend-following strategy; PTFSFX is the return of currency primitive trend-following strategy; and PTFSCOM is the return of commodity primitive trend-following strategy. We report the results for four samples: all funds, funds with AUM of more than $10 million, funds that exclude funds-of-funds, and funds-of-funds.

Sample Period	All Funds (% per month)	Funds with AUM $>$ 10m (% per month)	Excluding FoFs (% per month)	Funds-of-Funds (% per month)
Full Sample				
1994–2005	0.29	0.33	0.34	0.10
Sub-samples				
1994–1996	0.49	0.53	0.52	0.24
1997–1999	0.47	0.54	0.46	0.54
2000–2002	0.37	0.37	0.41	0.22
2003–2005	0.07	0.07	0.11	−0.03

Table 5.5: Distribution of Individual Hedge Fund Alpha

Cross-sectional statistics of individual hedge fund alphas (percent per month). We implement the seven-factor model for each fund and then calculate the cross-sectional statistics across funds. For each fund, the dependent variable used in the time-series regression is net-of-fee return. The independent variables are as follows: SNPMRF is the S&P 500 return minus risk-free rate; SCMLC is the Wilshire small cap return minus large cap return; BD10RET is the change in the 10-year treasury constant maturity yield; BAAMTSY is the change in the Moody's Baa yield less 10-year treasury constant maturity yield; PTFSBD is the return of bond primitive trend-following strategy; PTFSFX is the return of currency primitive trend-following strategy; and PTFSCOM is the return of commodity primitive trend-following strategy. We report the results for four samples: all funds, funds with AUM of more than $10 million, funds that exclude funds-of-funds, and funds-of-funds.

Panel A: All Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−1.59	−0.90	−0.24	0.37	1.05	2.03	3.03
1997–1999	−1.96	−1.18	−0.34	0.32	1.08	2.28	3.35
2000–2002	−1.62	−0.82	−0.17	0.30	0.86	1.79	2.52
2003–2005 (Last)	−1.70	−1.05	−0.30	0.08	0.52	1.14	1.70
Last – First	−0.10	−0.15	−0.06	−0.28	−0.54	−0.89	−1.33

Panel B: Funds with AUM>10M

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−1.08	−0.57	−0.08	0.38	0.98	1.85	2.67
1997–1999	−1.34	−0.87	−0.19	0.38	1.03	2.14	2.93
2000–2002	−1.18	−0.67	−0.08	0.33	0.83	1.66	2.30
2003–2005 (Last)	−1.41	−0.85	−0.24	0.11	0.52	1.07	1.58
Last – First	−0.33	−0.28	−0.16	−0.27	−0.46	−0.78	−1.08

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Table 5.5: continued

Panel C: Excluding Funds-of-Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−1.67	−1.00	−0.25	0.41	1.20	2.18	3.10
1997–1999	−2.03	−1.27	−0.42	0.27	1.12	2.48	3.58
2000–2002	−1.84	−0.96	−0.26	0.35	1.01	1.99	2.79
2003–2005 (Last)	−2.00	−1.28	−0.39	0.15	0.67	1.36	1.95
Last – First	−0.33	−0.28	−0.14	−0.25	−0.52	−0.82	−1.15

Panel D: Funds-of-Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−0.92	−0.55	−0.22	0.27	0.59	0.91	1.37
1997–1999	−0.90	−0.23	0.13	0.46	0.98	1.67	2.04
2000–2002	−0.55	−0.29	0.01	0.25	0.45	0.70	0.92
2003–2005 (Last)	−0.92	−0.54	−0.23	0.00	0.22	0.48	0.71
Last – First	0.00	0.01	−0.02	−0.28	−0.37	−0.44	−0.67

** and * denote significance at the 5% and 10% levels, respectively.

Table 5.6: Quantile Regression Analysis of Individual Hedge Fund Alpha

Coefficient estimates and t-statistics (in parentheses) of quantile regression of individual hedge fund alpha on fund characteristics. The resampling method of He and Hu (2002) is used to compute confidence intervals for parameter estimates. We first calculate each hedge fund's alpha using the seven-factor model. Then, we run quantile regression of alpha on fund characteristics. The explanatory variables are as follows: Fund Size is the logarithm of AUM of each fund; Fund Age is the number of years from a fund's inception date to the last date it appears in the sample; Use of Leverage is an indicator variable for whether a fund uses leverage; Use of Derivatives is an indicator variable for whether a fund uses derivatives; High Water Mark is an indicator variable for whether a fund has a high water market clause; Hurdle Rate is an indicator variable for whether a fund has a hurdle rate clause; Incentive Fee is the percentage of incentive fee; Management Fee is the percentage of management fee; Lock Up is an indicator variable for whether a fund has a lockup period; Redemption Notice Period is the redemption notice period (in 30-day units); Early Redemption Fee is an indicator variable for whether a fund charges an early redemption fee. On Shore is an indicator variable for whether a fund has an onshore organization. Strategy Dummies are the dummy variables for the nine strategies (with the unspecified strategy group being dropped). The sample period extends from January 1994 through December 2005.

	5^{th}Quantile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Quantile
Intercept	-6.12^{**}	-3.74^{**}	-2.15^{**}	-1.04^{**}	0.06	1.79^{**}	2.77^{**}
	(−9.41)	(−10.68)	(−10.16)	(−7.14)	(0.28)	(5.22)	(4.69)
Fund Size	0.26^{**}	0.17^{**}	0.10^{**}	0.06^{**}	0.02^{**}	-0.04^{**}	-0.07^{**}
	(14.06)	(15.78)	(13.30)	(12.15)	(3.25)	(−3.19)	(−3.58)
Fund Age	0.06^{**}	0.05^{**}	0.03^{**}	0.02^{**}	0.00	-0.02^{**}	-0.03^{**}
	(11.14)	(19.23)	(16.40)	(9.34)	(1.18)	(−4.83)	(−7.00)
Use of Leverage	0.03	−0.05	−0.05	0.05	0.15^{**}	0.14	0.30
	(0.17)	(−0.49)	(−0.78)	(0.81)	(2.16)	(1.11)	(1.39)
Use of Derivatives	0.08	0.04	0.01	0.02	0.04^{*}	0.09^{**}	0.11^{**}
	(1.14)	(1.01)	(0.54)	(1.46)	(1.70)	(2.07)	(2.02)

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Table 5.6: continued

	5^{th}Quantile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Quantile
High Water Mark	0.08	0.12	0.17**	0.11**	0.10**	0.27**	0.27**
	(0.44)	(1.29)	(3.42)	(2.58)	(1.76)	(2.75)	(2.49)
Hurdle Rate	−0.02	−0.19*	−0.23**	−0.09	−0.13	−0.18	−0.15
	(−0.03)	(−1.70)	(−2.30)	(−0.94)	(−1.15)	(−0.86)	(−0.21)
Incentive Fee	0.00	0.01**	0.01**	0.01**	0.02**	0.02**	0.02**
	(0.36)	(2.82)	(4.56)	(6.48)	(9.90)	(5.84)	(4.93)
Management Fee	−0.04	−0.05**	−0.03	−0.01	−0.01	0.00	−0.02
	(−1.03)	(−3.81)	(−1.48)	(−0.74)	(−1.17)	(−0.20)	(−0.57)
Lock Up	−0.04	−0.03	0.06	0.06	0.14**	0.09	−0.01
	(−0.25)	(−0.31)	(1.25)	(1.51)	(3.32)	(1.41)	(−0.07)
Redemption Notice Period	0.07**	0.05**	0.05**	0.06**	0.07**	0.08**	0.06**
	(3.33)	(2.60)	(3.35)	(6.17)	(6.03)	(3.61)	(2.16)
Minimum Investment	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(−0.02)	(−0.07)	(−0.11)	(−0.06)	(−0.05)
Early Redemption Fee	−0.07	0.16	0.09	0.04	−0.04	−0.06	−0.06
	(−0.27)	(1.16)	(1.46)	(0.81)	(−0.62)	(−0.64)	(−0.39)
On Shore	0.24**	0.15**	0.12**	0.10**	0.07**	0.11**	0.25**
	(3.32)	(3.65)	(4.21)	(5.33)	(2.67)	(2.14)	(3.84)
Strategy Dummies	included	included	included	included	included	included	included

** and * denote significance at the 5% and 10% levels, respectively.

Table 5.7: Regression Analysis of Fund Flow on Alpha

Coefficient estimates and t-statistics (in parentheses) of Fama-Macbeth (1973) regression of monthly fund flow (percent per month) on lagged performance variables. Based on the seven-factor model, we estimate alpha using return data in the previous 24 months. The regression is run separately for each performance quintile. The dependent variable is the monthly flow for each fund. The independent variables are as follows: An intercept that represents the baseline flow for each quintile group; the performance rank within each quintile (ranging from 0 to 1); and the lagged flow in the previous month. Newey and West (1987) standard errors (with 24 lags) are used to compute the standard errors of a time-series of coefficients from the 120 monthly cross-sectional regressions. The sample period extends from January 1994 through December 2005. We report the results for four samples: all funds, funds with AUM of more than $10 million, funds that exclude funds-of-funds, and funds-of-funds.

Panel A: All Funds

	Group 1 (smallest alpha)	Group 2	Group 3	Group 4	Group 5 (largest alpha)
Intercept (Base flow for each group)	-1.82^{**}	-0.86^{**}	-0.21	-0.50^{**}	1.05^{**}
	(-13.93)	(-5.87)	(-1.17)	(2.43)	(4.29)
Performance Rank within Each Group	0.75^{**}	0.56^{**}	0.77^{**}	0.56^{**}	0.67^{**}
	(4.35)	(2.04)	(5.83)	(3.47)	(2.82)
Lagged Flow	0.01^{*}	0.04^{**}	0.04^{**}	0.04^{**}	0.04^{**}
	(1.97)	(7.93)	(4.52)	(5.27)	(4.80)

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Table 5.7: continued

Panel B: Funds with AUM>10M

	Group 1 (smallest alpha)	Group 2	Group 3	Group 4	Group 5 (largest alpha)
Intercept (Base flow for each group)	−1.78**	−0.74**	0.00	0.70**	1.34**
	(−11.69)	(−4.39)	(−0.01)	(2.83)	(4.91)
Performance Rank within Each Group	0.93**	0.74**	0.73**	0.67**	0.91**
	(3.89)	(2.85)	(4.99)	(3.20)	(2.77)
Lagged Flow	0.04**	0.08**	0.07**	0.08**	0.06**
	(7.11)	(9.44)	(5.25)	(8.73)	(4.96)

Panel C: Excluding Funds-of-Funds

	Group 1 (smallest alpha)	Group 2	Group 3	Group 4	Group 5 (largest alpha)
Intercept (Base flow for each group)	−1.92**	−1.00**	−0.39**	0.40**	1.00**
	(−14.12)	(−5.66)	(−2.07)	(2.13)	(4.80)
Performance Rank within Each Group	0.69**	0.58*	0.94**	0.63**	0.76**
	(3.78)	(1.83)	(6.85)	(4.35)	(3.48)
Lagged Flow	0.01*	0.03**	0.04**	0.05**	0.05**
	(1.88)	(6.08)	(4.34)	(5.08)	(5.53)

Continued on next page

Table 5.7: continued

Panel D: Funds-of-Funds

	Group 1 (smallest alpha)	Group 2	Group 3	Group 4	Group 5 (largest alpha)
Intercept (Base flow for each group)	−1.52**	−0.41**	0.59**	0.88**	1.15**
	(−6.45)	(−1.98)	(2.76)	(2.74)	(2.51)
Performance Rank within Each Group	1.11**	0.64**	−0.16	0.14	0.24
	(3.38)	(2.85)	(−0.37)	(0.31)	(0.51)
Lagged Flow	0.00	0.08**	0.08**	0.08**	0.01
	(0.06)	(3.62)	(4.35)	(4.14)	(0.32)

** and * denote significance at the 5% and 10% levels, respectively.

Table 5.8: Tests of Capacity Constraints: Fund-Level vs. Strategy-Level Constraints

Coefficient estimates and t-statistics (in parentheses) of the panel regression of alpha (percent per month) on lagged fund-level variables and lagged strategy-level variables. Rogers (1993) standard errors are used to control for the clustering effects of the cross-sectional correlation across funds. The dependent variable is the individual fund's risk-adjusted return estimated by using an out-of-sample method. In each month, risk-adjusted return is equal to return minus the realization of factors times the factor loadings calculated using data in the previous 24 months. The independent variables are as follows: Fund Flow is the flow into each fund in the previous 12 months; Fund Size is the logarithm of AUM of each fund at the end of the previous month; Large Fund Dummy is an indicator variable that takes value 1 (0) if the fund's AUM is larger (smaller) than the median size of the funds in its strategy category in the beginning period of calculating the fund flow. Strategy Flow is the aggregate flow into the strategy (to which the fund belongs) in the previous 12 months; Strategy Size is the logarithm of the total AUM of the strategy at the end of the previous month. Number of Funds is the total number of funds in each strategy in the previous month. The sample period extends from January 1994 through December 2005.

	1	2	3	4	5	6	7	8	9	10
Intercept	0.26**	−2.48	−1.90	0.40**	5.98**	0.72**	−0.99	0.41**	1.45	−1.74
	(2.26)	(−1.58)	(−1.17)	(2.51)	(2.84)	(4.15)	(−0.34)	(2.61)	(0.39)	(−0.52)
Fund-Level										
Fund Flow	0.44**		0.42**					0.55**		0.46**
	(2.48)		(2.44)					(3.30)		(2.87)
Fund Flow×Large Fund Dummy	−0.63**		−0.60**					−0.59**		−0.52**
	(−3.41)		(−3.31)					(−3.62)		(−3.02)
Fund Size		0.32*	0.25						0.13	0.08
		(1.79)	(1.36)						(0.81)	(0.51)
Fund Size^2		−0.01*	−0.01						0.00	0.00
		(−1.80)	(−1.38)						(−0.86)	(−0.60)
Strategy-Level										
Strategy Flow				−0.95*			−1.16**	−0.97*		−1.17**
				(−1.77)			(−2.28)	(−1.82)		(−2.32)
Strategy Size					−0.23**		0.08		−0.08	0.09
					(−2.72)		(0.65)		(−0.51)	(0.71)
Number of Funds						−0.10**	−0.12**		−0.08	−0.13**
						(−2.55)	(−2.22)		(−1.33)	(−2.23)

** and * denote significance at the 5% and 10% levels, respectively.

Table 5.9: Tests of Capacity Constraints for Different Strategies

Coefficient estimates and t-statistics (in parentheses) of the panel regression of alpha (percent per month) on lagged fund-level variables and lagged strategy level variables. Rogers (1993) standard errors are used to control for the clustering effects of the cross-sectional correlation across funds. The regression is run separately for funds in each strategy. The dependent variable is the individual fund's risk-adjusted return estimated using an out-of-sample method. In each month, risk-adjusted return is equal to return minus the realization of factors times the factor loadings calculated, using data in the previous 24 months. The independent variables are as follows: Fund Flow is the capital flow into each fund in the previous 12 months; Large Fund Dummy is an indicator variable that takes value 1 (0) if the fund's AUM is larger (smaller) than the median size of the funds in its strategy category in the beginning period of calculating the fund flow. Strategy Flow is the aggregate capital flow into the strategy (to which the fund belongs) in the previous 12 months. The sample period extends from January 1994 through December 2005. We report results for nine hedge fund strategies.

	Security Selection	Relative Values	Managed Futures	Multi-Process	Directional Trading	Emerging Markets	Macro	FoFs	Others
Intercept	0.41**	0.49**	0.10	0.43**	0.21*	0.72**	0.15	0.57**	0.48**
	(3.99)	(4.13)	(0.32)	(3.19)	(1.76)	(2.24)	(1.25)	(4.39)	(3.65)
Fund Flow	0.41**	0.33**	0.45**	0.14	0.45**	0.38	0.20	0.10	0.50*
	(4.25)	(2.53)	(2.56)	(1.21)	(2.37)	(1.16)	(0.91)	(1.51)	(1.90)
Fund Flow×Large Fund Dummy	−0.30**	−0.13	−0.50**	−0.27**	−0.48*	−0.76*	−0.20	−0.13*	−0.31
	(−2.89)	(−0.96)	(−2.73)	(−2.08)	(−1.91)	(−1.88)	(−0.68)	(−1.85)	(−0.84)
Strategy Flow	−0.87*	−0.91**	−2.16*	−0.35	0.63	0.66	−0.12	−1.02**	−0.74**
	(−1.76)	(−2.29)	(−1.76)	(−0.80)	(1.25)	(0.89)	(−0.42)	(−2.78)	(−2.44)

** and * denote significance at the 5% and 10% levels, respectively.

Table 5.10: Cross-sectional Difference of Capacity Constraint Sensitivity

Coefficient estimates and t-statistics (in parentheses) of OLS regression of alpha-flow sensitivity (the relation between alpha and fund-level flow) on fund characteristics. White (1980) heteroskedasticity-robust standard errors are used to calculate the t-statistics. We first calculate each hedge fund's alpha-flow sensitivity by running fund-by-fund time-series regression of risk-adjusted return on lagged fund-level flow and lagged strategy-level flow, then we run OLS regressions using the coefficients of fund-level flow from the previous step on fund characteristics. The explanatory variables are as follows: Fund Size is the logarithm of AUM of each fund; Use of Leverage is an indicator variable for whether a fund uses leverage; Incentive Fee is the percentage of incentive fee; Management Fee is the percentage of management fee. Lock Up is an indicator variable for whether a fund has a lockup period; Redemption Notice Period is the redemption notice period (in 30-day units); Strategy Dummies are the dummy variables for the nine strategies (with the unspecified strategy group being dropped). The sample period extends from January 1994 through December 2005.

	1	2	3	4	5	6
Intercept	1.98*	0.34*	−0.36	2.84*	2.90*	2.89*
	(1.67)	(1.69)	(−1.45)	(1.76)	(1.81)	(1.80)
Fund Size	−0.12*			−0.17**	−0.16**	−0.16**
	(−1.79)			(−2.40)	(−2.35)	(−2.34)
Management Fee		−0.26**		−0.25*	−0.25**	−0.25**
		(−2.16)		(−1.97)	(−1.97)	(−1.97)
Incentive Fee			0.02	0.03	0.03	0.03
			(1.24)	(1.59)	(1.59)	(1.60)
Lock Up					−0.21	−0.18
					(−0.44)	(−0.37)
Redemption Notice Period					−0.12	−0.12
					(−0.96)	(−0.96)
Use of Leverage						−0.12
						(−0.22)
Strategy Dummies	–	–	–	included	included	included

** and ** denote significance at the 5% and 10% levels, respectively.

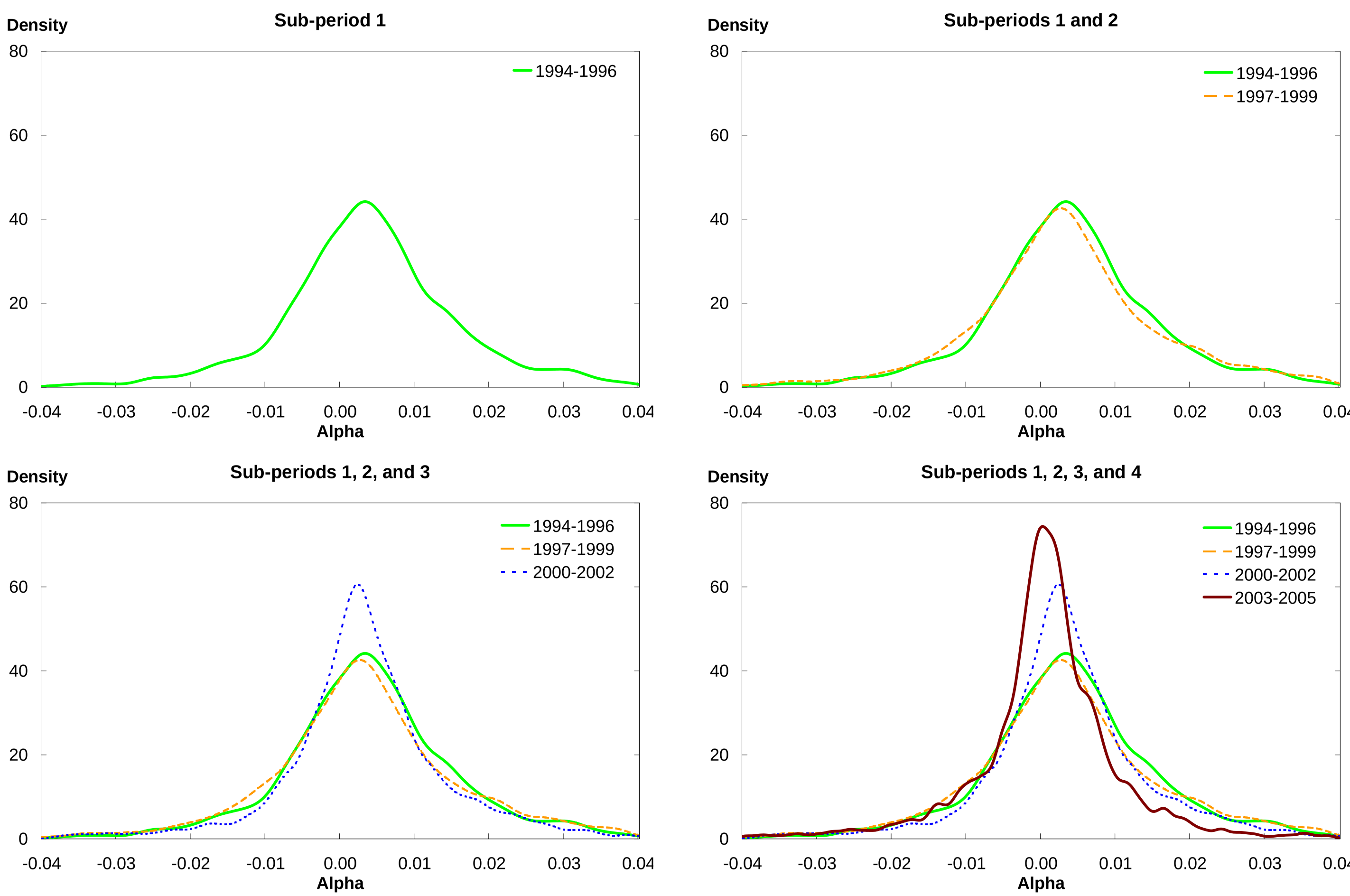


Figure 5.1: Evolution of the distribution of individual hedge fund alpha. This figure plots the empirical density functions of individual hedge fund alphas (estimated using the seven-factor model) over four sub-periods. The total sample period extends from January 1994 through December 2005.

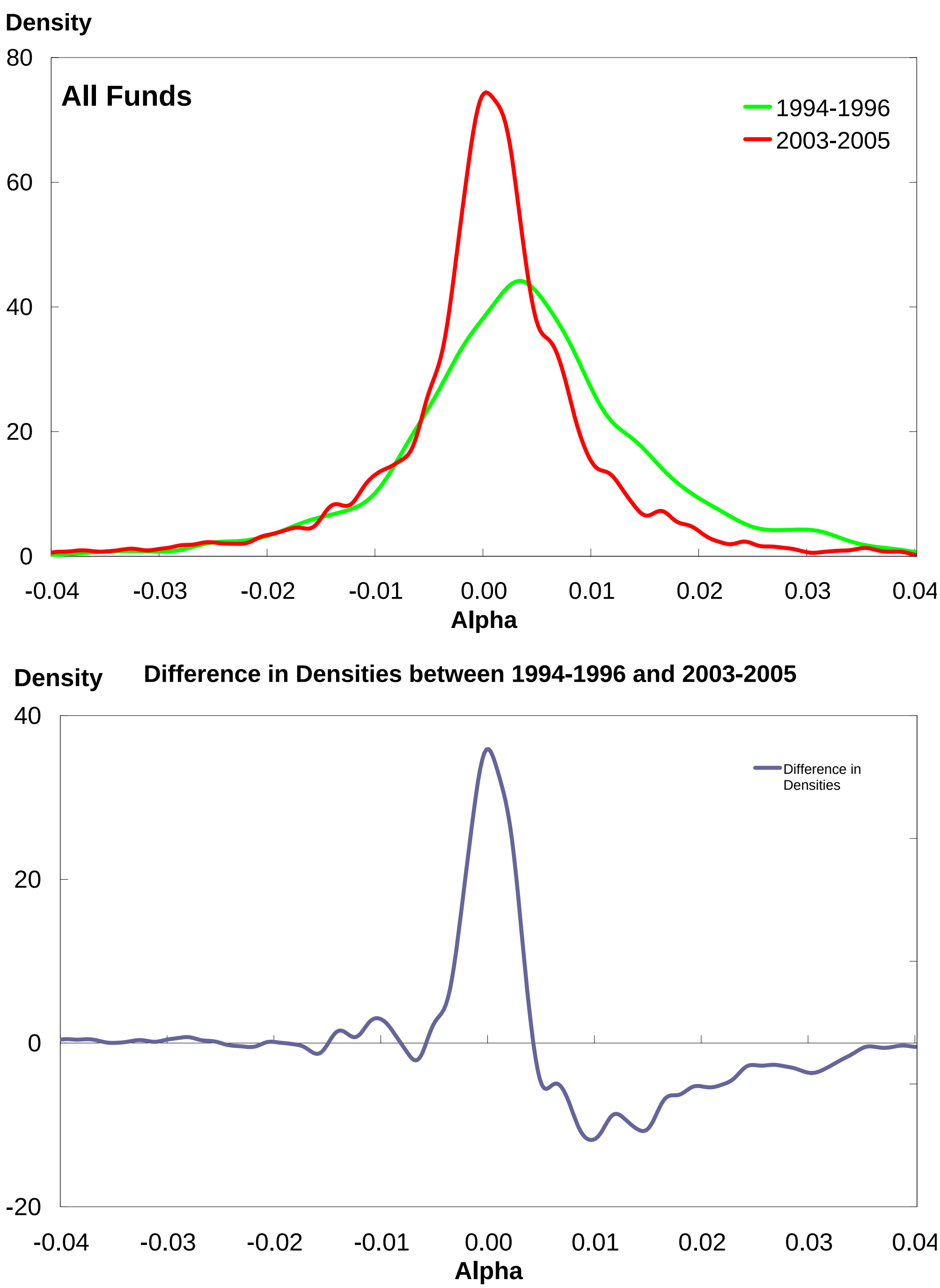


Figure 5.2: Comparison of alphas in the first and last periods—all funds. The upper panel plots the empirical density functions of alphas of all funds during the first period (1994-1996) and the last period (2003-2005). The lower panel plots the difference between the two densities.

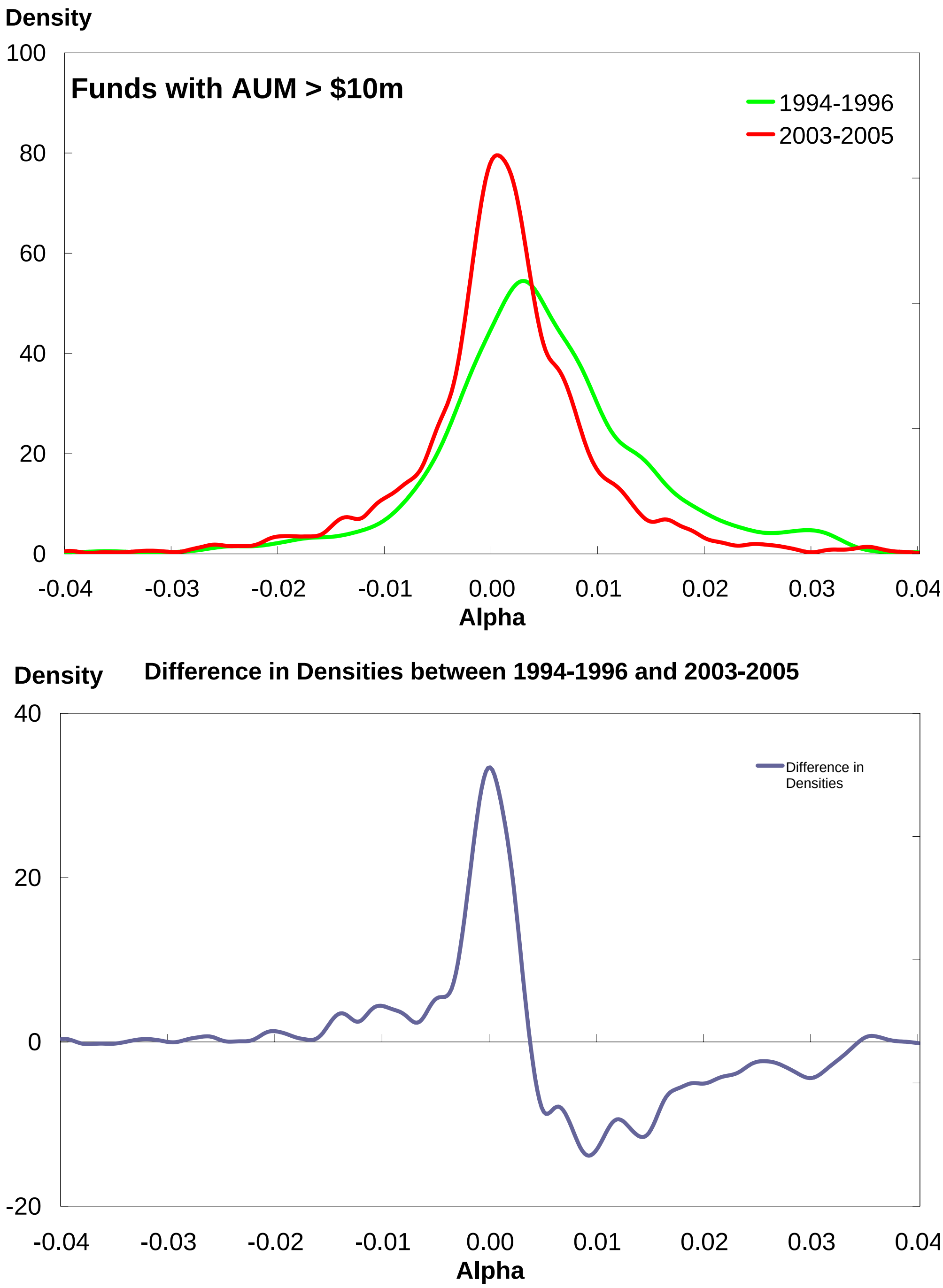
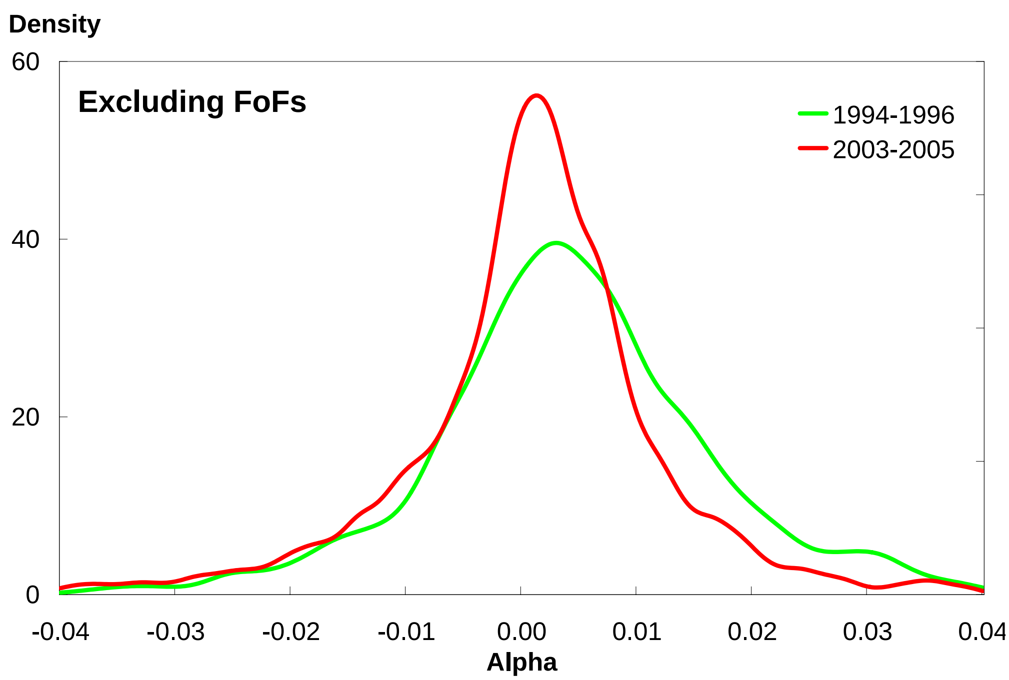


Figure 5.3: Comparison of alphas in the first and last periods—AUM > $10m. The upper panel plots the empirical density functions of alphas of funds with assets under management (AUM) of more than $10 million during the first period (1994-1996) and the last period (2003-2005). The lower panel plots the difference between the two densities.



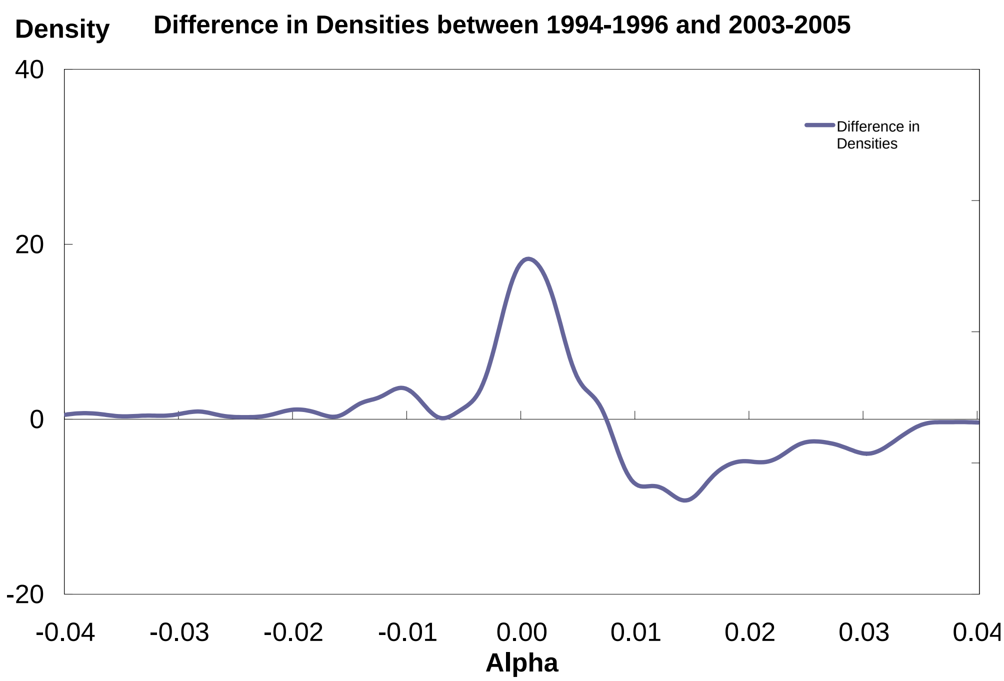


Figure 5.4: Comparison of alphas in the first and last periods—Exclude FoFs. The upper panel plots the empirical density functions of alphas of funds that are not funds-of-funds (FoFs) during the first period (1994-1996) and the last period (2003-2005). The lower panel plots the difference between the two densities.

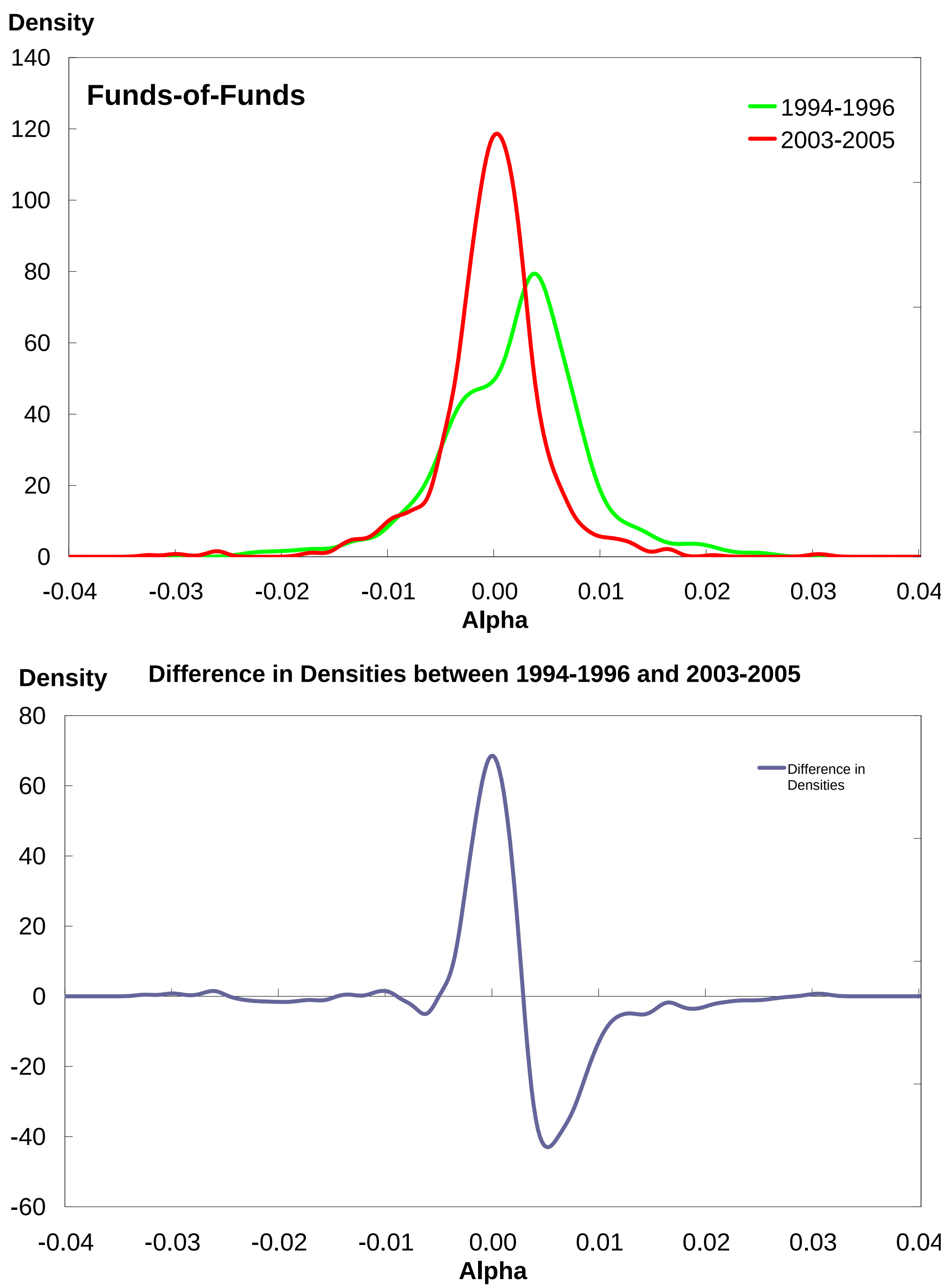


Figure 5.5: Comparison of alphas in the first and last periods—FoFs. The upper panel plots the empirical density functions of alphas of funds-of-funds (FoFs) during the first period (1994-1996) and the last period (2003-2005). The lower panel plots the difference between the two densities.

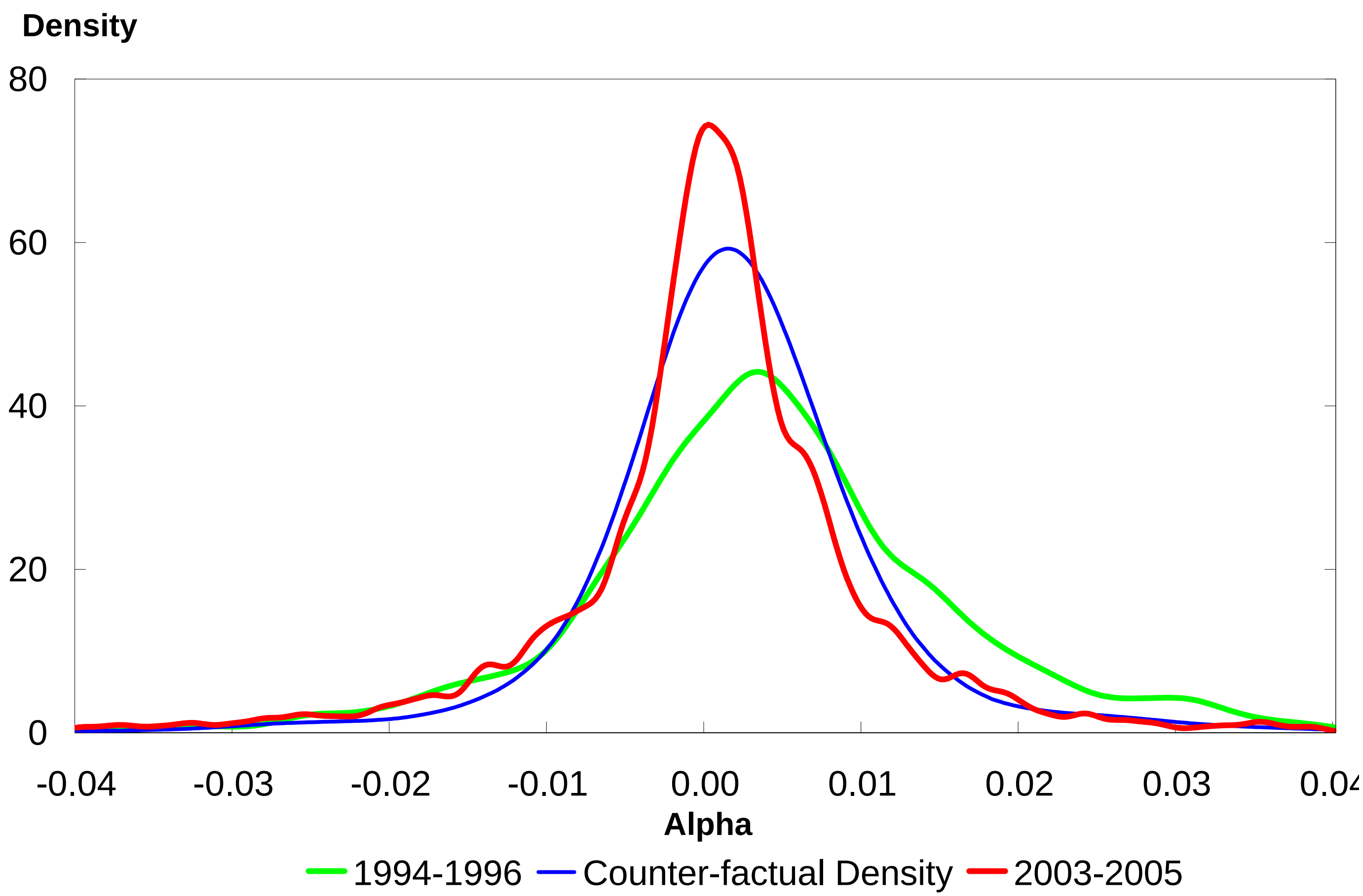


Figure 5.6: Counter-factual density of individual hedge fund alpha. This figure plots the counter-factual density of hedge fund alpha in 2003-2005, assuming that the fund characteristics have remained unchanged since 1994-1996. The difference between the actual density of 2003-2005 and the counter-factual density represents the change in characteristics effect. The difference between the counter-factual density and the actual density of 1994-1996 represents the change in market conditions effect.

Chapter 6

Robustness Checks

In this chapter, we perform several additional tests to confirm the robustness of our empirical results.

6.1 Augmented Factor Model

Every empirical analysis using an asset pricing model is essentially a joint-test of the theories being tested and the asset pricing model itself. To address this concern, we augment the seven-factor model of Fung and Hsieh (2004b) with factors from alternative asset pricing models. Given the success of Fama-French-Carhart 4-factor model [Carhart (1997)] in explaining mutual fund returns, we include the High-Minus-Low factor and Momentum factor as additional factors in the estimation of hedge fund alpha. We find that our results are robust using the augmented factor model (see Table 6.1 and Figure 6.1).

6.2 Controlling for Incubation Bias

To control for the incubation bias (also known as backfill bias and instant history bias), we delete the first 12 months of data for each hedge fund and then repeat our analysis. Table 6.1 reports the percentiles of hedge fund alphas after controlling for the incubation bias. We find that the results are similar to those in Table 5.5. For example, for the case of all funds, the change in 95th percentile is -1.15% (from 2.80% during 1994-1996 to 1.66% during 2003-2005), while the change in the 5th percentile is -0.27% (from -1.64% during 1994-1996 to -1.91% during 2003-2005). The comparison of empirical densities of the first and last sub-periods again confirms the robustness of our findings (see Figure 6.2).

6.3 Alternative Sub-sample Periods

When examining the evolution of the distribution of hedge fund alpha, we also divide our sample into six even sub-periods: 1994-1995, 1996-1997, 1998-1999, 2000-2001, 2002-2003, and 2004-2005. The shorter sub-sample period introduces more noise in the estimation of alpha, yet the findings are similar to the results using four sub-periods (see Table 6.3 and Figure 6.3).

6.4 Alternative Estimation Windows in Estimating Out-of-sample Alphas

When conducting analysis of the alpha-flow relations that involve rolling-window estimation, we use alternative estimation windows of 12 or 36 months. We confirm that our results are unaffected by the choice of window length (see Table 6.4 for the results of using a 12-month estimation window and Table 6.5 for the results of using a 36-month estimation window).

Table 6.1: Distribution of Alpha using Augmented Factor Model

Cross-sectional statistics of individual hedge fund alphas (percent per month). We augment the seven-factor model [Fung and Hsieh (2004b)] with the High-Minus-Low factor (HML) and the Momentum factor (Mom) from the Fama-French-Carhart 4-factor model [Carhart (1997)]. We implement the augmented factor model for each fund and then calculate the cross-sectional statistics across funds. For each fund, the dependent variable used in the time-series regression is net-of-fee return. The independent variables are as follows: SNPMRF is the S&P 500 return minus risk-free rate; SCMLC is the Wilshire small cap return minus large cap return; BD10RET is the change in the 10-year treasury constant maturity yield; BAAMTSY is the change in the Moody's Baa yield less 10-year treasury constant maturity yield; PTFSBD is the return of bond primitive trend-following strategy; PTFSFX is the return of currency primitive trend-following strategy; and PTFSCOM is the return of commodity primitive trend-following strategy; HML is the average return on the two value portfolios (that is, with high BE/ME ratios) minus the average return on the two growth portfolios (low BE/ME ratios); and Mom is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. Reported below are the results for all funds.

Panel A: All Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−1.78	−1.07	−0.23	0.39	1.13	2.31	3.30
1997–1999	−2.24	−1.31	−0.38	0.30	1.07	2.31	3.29
2000–2002	−1.49	−0.80	−0.16	0.30	0.90	1.82	2.61
2003–2005 (Last)	−1.68	−1.03	−0.31	0.08	0.51	1.14	1.76
Last − First	0.10	0.03	−0.08	−0.31	−0.62	−1.17	−1.54

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Table 6.1: continued

Panel B: Funds with AUM>10M

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−1.19	−0.61	−0.05	0.42	1.03	1.92	2.84
1997–1999	−1.51	−0.92	−0.25	0.37	1.02	1.98	2.85
2000–2002	−1.17	−0.63	−0.10	0.32	0.85	1.58	2.27
2003–2005 (Last)	−1.41	−0.90	−0.25	0.11	0.50	1.07	1.57
Last – First	−0.22	−0.29	−0.21	−0.32	−0.53	−0.85	−1.27

Panel C: Excluding Funds-of-Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−1.96	−1.14	−0.22	0.46	1.27	2.46	3.44
1997–1999	−2.33	−1.40	−0.48	0.26	1.14	2.46	3.52
2000–2002	−1.73	−0.94	−0.24	0.36	1.05	2.06	2.88
2003–2005 (Last)	−1.99	−1.25	−0.41	0.14	0.68	1.38	2.08
Last – First	−0.02	−0.10	−0.18	−0.32	−0.60	−1.08	−1.35

Panel D: Funds-of-Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−1.08	−0.71	−0.26	0.22	0.52	0.90	1.25
1997–1999	−1.13	−0.35	0.13	0.42	0.91	1.46	1.80
2000–2002	−0.63	−0.35	−0.01	0.23	0.45	0.71	1.05
2003–2005 (Last)	−0.89	−0.55	−0.23	0.01	0.23	0.46	0.69
Last – First	0.19	0.16	0.03	−0.21	−0.29	−0.44	−0.55

** and * denote significance at the 5% and 10% levels, respectively.

Table 6.2: Distribution of Alpha after Controlling for Incubation Bias

Cross-sectional statistics of individual hedge fund alphas (percent per month). In order to control for incubation bias, we delete the first 12 months of data for each hedge fund. We implement the seven-factor model for each fund and then calculate the cross-sectional statistics across funds. For each fund, the dependent variable used in the time-series regression is net-of-fee return. The independent variables are as follows: SNPMRF is the S&P 500 return minus risk-free rate; SCMLC is the Wilshire small cap return minus large cap return; BD10RET is the change in the 10-year treasury constant maturity yield; BAAMTSY is the change in the Moody's Baa yield less 10-year treasury constant maturity yield; PTFSBD is the return of bond primitive trend-following strategy; PTFSFX is the return of currency primitive trend-following strategy; and PTFSCOM is the return of commodity primitive trend-following strategy. Reported below are the results for all funds.

Panel A: All Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−1.64	−0.96	−0.27	0.30	0.97	1.92	2.80
1997–1999	−2.09	−1.29	−0.44	0.25	0.95	2.08	2.97
2000–2002	−1.59	−0.85	−0.22	0.28	0.81	1.71	2.47
2003–2005 (Last)	−1.91	−1.15	−0.35	0.06	0.50	1.11	1.66
Last – First	−0.27	−0.19	−0.09	−0.24	−0.47	−0.81	−1.15

Panel B: Funds with AUM>10M

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−1.18	−0.62	−0.09	0.35	0.93	1.73	2.43
1997–1999	−1.35	−0.95	−0.25	0.36	1.00	2.05	2.85
2000–2002	−1.18	−0.73	−0.13	0.30	0.78	1.61	2.25
2003–2005 (Last)	−1.55	−0.96	−0.26	0.09	0.50	1.06	1.55
Last – First	−0.37	−0.34	−0.17	−0.26	−0.43	−0.67	−0.87

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Table 6.2: continued

Panel C: Excluding Funds-of-Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−1.83	−1.10	−0.30	0.30	1.06	1.99	2.88
1997–1999	−2.18	−1.33	−0.55	0.17	0.93	2.14	3.10
2000–2002	−1.77	−0.97	−0.30	0.29	0.92	1.92	2.71
2003–2005 (Last)	−2.20	−1.38	−0.42	0.11	0.64	1.29	1.87
Last – First	−0.36	−0.28	−0.12	−0.19	−0.42	−0.70	−1.01

Panel D: Funds-of-Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1996 (First)	−0.70	−0.48	−0.09	0.27	0.62	0.91	1.32
1997–1999	−1.39	−0.41	0.11	0.45	0.99	1.77	2.36
2000–2002	−0.66	−0.34	0.00	0.27	0.45	0.69	0.92
2003–2005 (Last)	−0.95	−0.67	−0.23	0.00	0.21	0.47	0.67
Last – First	−0.25	−0.19	−0.14	−0.27	−0.40	−0.44	−0.64

** and * denote significance at the 5% and 10% levels, respectively.

Table 6.3: Distribution of Alpha using Alternative Sub-sample Periods

Cross-sectional statistics of individual hedge fund alphas (percent per month) of alternative sub-sample periods. We implement the seven-factor model for each fund and then calculate the cross-sectional statistics across funds. For each fund, the dependent variable used in the time-series regression is net-of-fee return. The independent variables are as follows: SNPMRF is the S&P 500 return minus risk-free rate; SCMLC is the Wilshire small cap return minus large cap return; BD10RET is the change in the 10-year treasury constant maturity yield; BAAMTSY is the change in the Moody's Baa yield less 10-year treasury constant maturity yield; PTFSBD is the return of bond primitive trend-following strategy; PTFSFX is the return of currency primitive trend-following strategy; and PTFSCOM is the return of commodity primitive trend-following strategy. Reported below are the results for all funds.

Panel A: All Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1995 (First)	−2.02	−1.16	−0.31	0.33	1.54	3.08	4.47
1996–1997	−2.52	−1.72	−0.73	0.15	0.80	1.62	2.50
1998–1999	−1.95	−1.10	−0.15	0.52	1.54	2.91	4.24
2000–2001	−1.96	−1.12	−0.24	0.38	1.00	2.04	2.97
2002–2003	−0.79	−0.42	0.03	0.40	0.97	1.74	2.34
2004–2005 (Last)	−1.93	−1.22	−0.51	−0.03	0.44	1.16	1.87
Last – First	0.08	−0.06	−0.20	−0.36	−1.10	−1.92	−2.60

Panel B: Funds with AUM>10M

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1995 (First)	−1.68	−0.94	−0.19	0.32	1.20	2.53	3.71
1996–1997	−1.71	−1.10	−0.41	0.33	0.83	1.53	2.33
1998–1999	−1.47	−0.81	−0.03	0.55	1.44	2.68	3.73
2000–2001	−1.45	−0.86	−0.08	0.42	0.99	1.93	2.77
2002–2003	−0.60	−0.23	0.09	0.40	0.92	1.60	2.09
2004–2005 (Last)	−1.65	−1.10	−0.45	−0.01	0.43	1.04	1.65
Last – First	0.03	−0.17	−0.26	−0.33	−0.77	−1.49	−2.06

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Table 6.3: continued

Panel C: Excluding Funds-of-Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1995 (First)	−2.27	−1.21	−0.31	0.42	1.69	3.31	4.77
1996–1997	−2.58	−1.84	−0.82	0.05	0.82	1.78	2.71
1998–1999	−2.04	−1.25	−0.26	0.49	1.59	3.15	4.40
2000–2001	−2.28	−1.25	−0.35	0.38	1.12	2.27	3.22
2002–2003	−0.91	−0.49	0.01	0.51	1.14	1.92	2.61
2004–2005 (Last)	−2.26	−1.48	−0.58	0.07	0.66	1.53	2.23
Last – First	0.01	−0.27	−0.27	−0.35	−1.02	−1.79	−2.54

Panel D: Funds-of-Funds

Sample Period	5^{th}Percentile	10^{th}	25^{th}	Median	75^{th}	90^{th}	95^{th}Percentile
1994–1995 (First)	−1.16	−1.01	−0.32	0.06	0.37	1.03	1.99
1996–1997	−1.35	−0.82	0.01	0.42	0.71	1.10	1.45
1998–1999	−0.93	−0.09	0.24	0.73	1.31	2.09	2.73
2000–2001	−0.86	−0.34	0.07	0.37	0.60	0.91	1.19
2002–2003	−0.31	−0.15	0.07	0.26	0.47	0.89	1.24
2004–2005 (Last)	−1.08	−0.77	−0.41	−0.12	0.15	0.42	0.62
Last – First	0.08	0.24	−0.08	−0.18	−0.23	−0.61	−1.37

** and * denote significance at the 5% and 10% levels, respectively.

Table 6.4: Tests of Capacity Constraints using 12-month Estimation Window

Coefficient estimates and t-statistics (in parentheses) of the panel regression of alpha (percent per month) on lagged fund-level variables and lagged strategy-level variables. Rogers (1993) standard errors are used to control for the clustering effects of the cross-sectional correlation across funds. The dependent variable is the individual fund's risk-adjusted return estimated by using an out-of-sample method. In each month, risk-adjusted return is equal to return minus the realization of factors times the factor loadings calculated, using data in the previous 12 months. The independent variables are as follows: Fund Flow is the flow into each fund in the previous 12 months; Fund Size is the logarithm of AUM of each fund at the end of the previous month; Large Fund Dummy is an indicator variable that takes value 1 (0) if the fund's AUM is larger (smaller) than the median size of the funds in its strategy category in the beginning period of calculating the fund flow. Strategy Flow is the aggregate flow into the strategy (to which the fund belongs) in the previous 12 months; Strategy Size is the logarithm of the total AUM of the strategy at the end of the previous month. Number of Funds is the total number of funds in each strategy in the previous month. The sample period extends from January 1994 through December 2005.

	1	2	3
Intercept	−1.70	3.28	4.42
	(−0.95)	(0.72)	(0.86)
Fund-Level			
Fund Flow	0.26		0.29
	(1.24)		(1.58)
Fund Flow×Large Fund Dummy	−0.73**		−0.59**
	(−3.66)		(−2.92)
Fund Size	−0.10		−0.21
	(−0.48)		(−1.08)
Fund Size^2	0.00		0.00
	(0.20)		(0.79)
Strategy-Level			
Strategy Flow		−1.32**	−1.31**
		(−2.30)	(−2.29)
Strategy Size		−0.10	−0.05
		(−0.49)	(−0.25)
Number of Funds		−0.05	−0.07
		(−0.70)	(−0.97)

** and ** denote significance at the 5% and 10% levels, respectively.

Table 6.5: Tests of Capacity Constraints using 36-month Estimation Window

Coefficient estimates and t-statistics (in parentheses) of the panel regression of alpha (percent per month) on lagged fund-level variables and lagged strategy-level variables. Rogers (1993) standard errors are used to control for the clustering effects of the cross-sectional correlation across funds. The dependent variable is the individual fund's risk-adjusted return estimated by using an out-of-sample method. In each month, risk-adjusted return is equal to return minus the realization of factors times the factor loadings calculated, using data in the previous 36 months. The independent variables are as follows: Fund Flow is the flow into each fund in the previous 12 months; Fund Size is the logarithm of AUM of each fund at the end of the previous month; Large Fund Dummy is an indicator variable that takes value 1 (0) if the fund's AUM is larger (smaller) than the median size of the funds in its strategy category in the beginning period of calculating the fund flow. Strategy Flow is the aggregate flow into the strategy (to which the fund belongs) in the previous 12 months; Strategy Size is the logarithm of the total AUM of the strategy at the end of the previous month. Number of Funds is the total number of funds in each strategy in the previous month. The sample period extends from January 1994 through December 2005.

	1	2	3
Intercept	−1.74	−1.99	−2.62
	(−1.03)	(−0.67)	(−0.77)
Fund-Level			
Fund Flow	0.40**		0.43**
	(2.20)		(2.46)
Fund Flow×Large Fund Dummy	−0.54**		−0.52**
	(−2.86)		(−2.98)
Fund Size	0.21		0.09
	(1.13)		(0.49)
Fund Size^2	−0.01		0.00
	(−1.04)		(−0.49)
Strategy-Level			
Strategy Flow		−0.59	−0.59
		(−1.18)	(−1.19)
Strategy Size		0.12	0.12
		(0.94)	(0.92)
Number of Funds		−0.10**	−0.10**
		(−2.07)	(−2.06)

** and ** denote significance at the 5% and 10% levels, respectively.

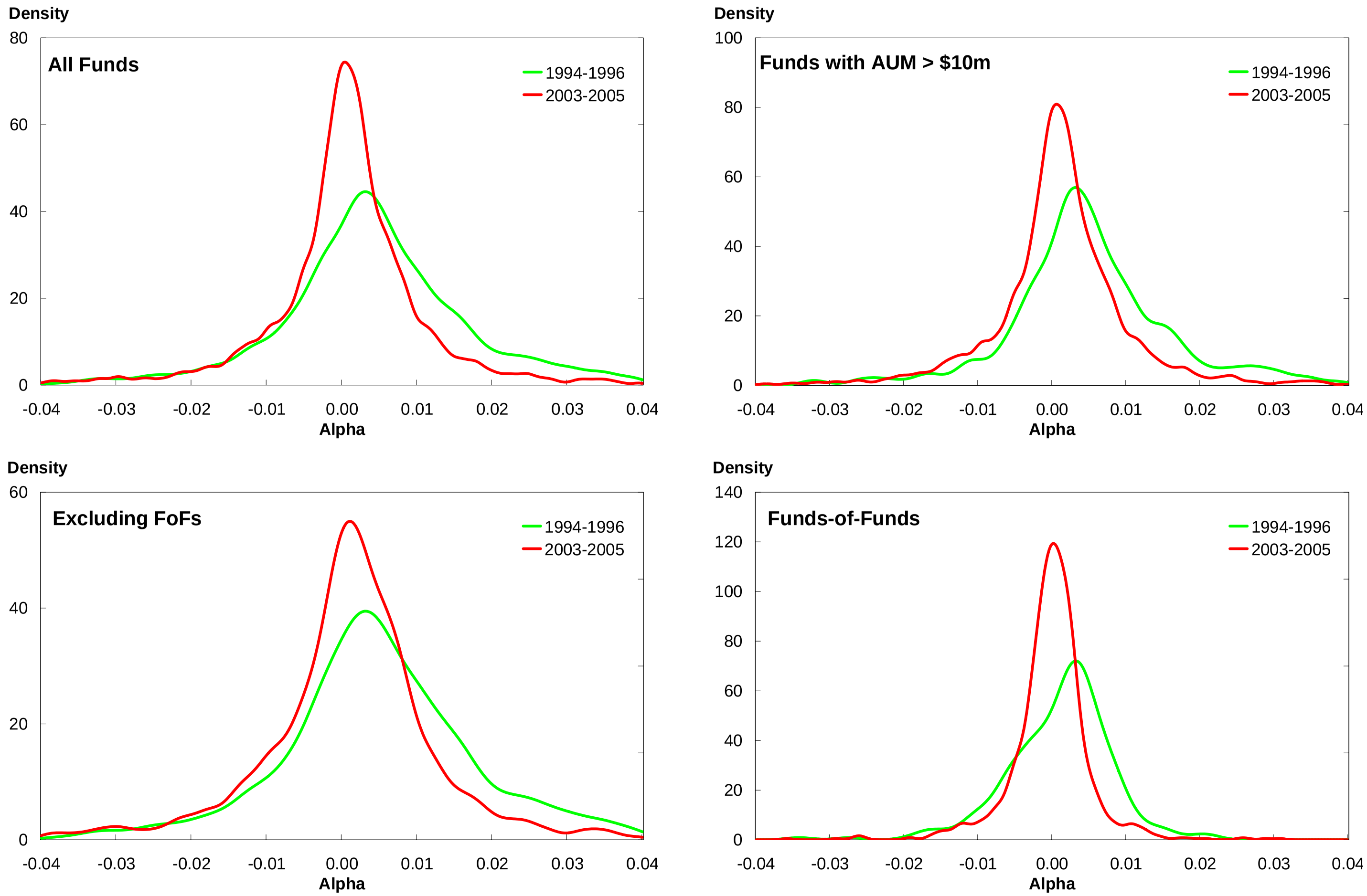

Figure 6.1: Distribution of alpha using augmented factor model. This figure plots the empirical density functions of individual hedge fund alphas (estimated using the seven-factor model augmented with HML and Mom factors) during the first period (1994-1996) and the last period (2003-2005). Four samples are considered: all funds, funds with AUM of more than $10 million, funds that are not funds-of-funds, and funds-of-funds.

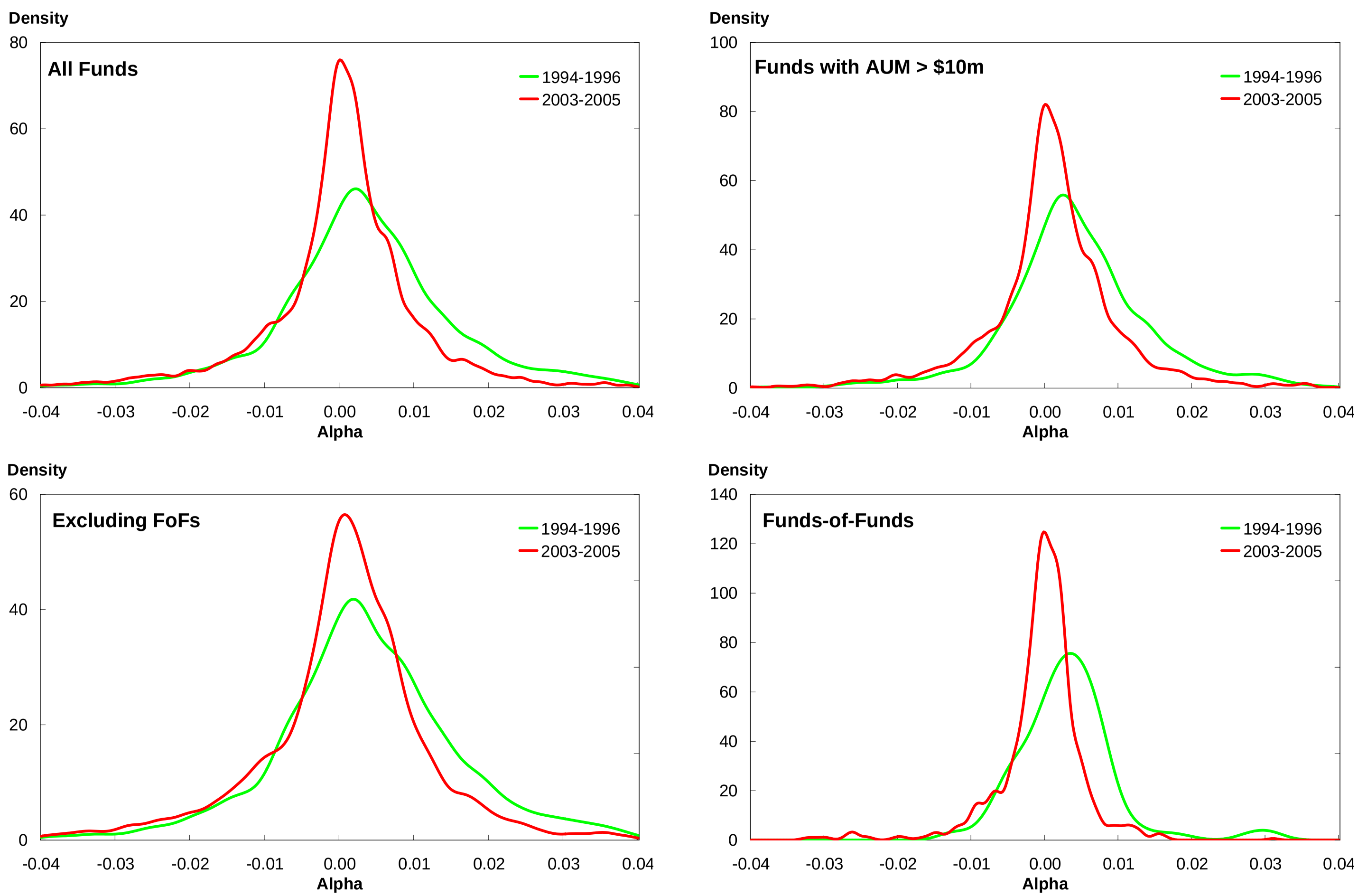

Figure 6.2: Distribution of alpha after controlling for incubation bias. This figure plots the empirical density functions of individual hedge fund alphas (estimated using the seven-factor model and after controlling for incubation bias) during the first period (1994-1996) and the last period (2003-2005). Four samples are considered: all funds, funds with AUM of more than $10 million, funds that are not funds-of-funds, and funds-of-funds.

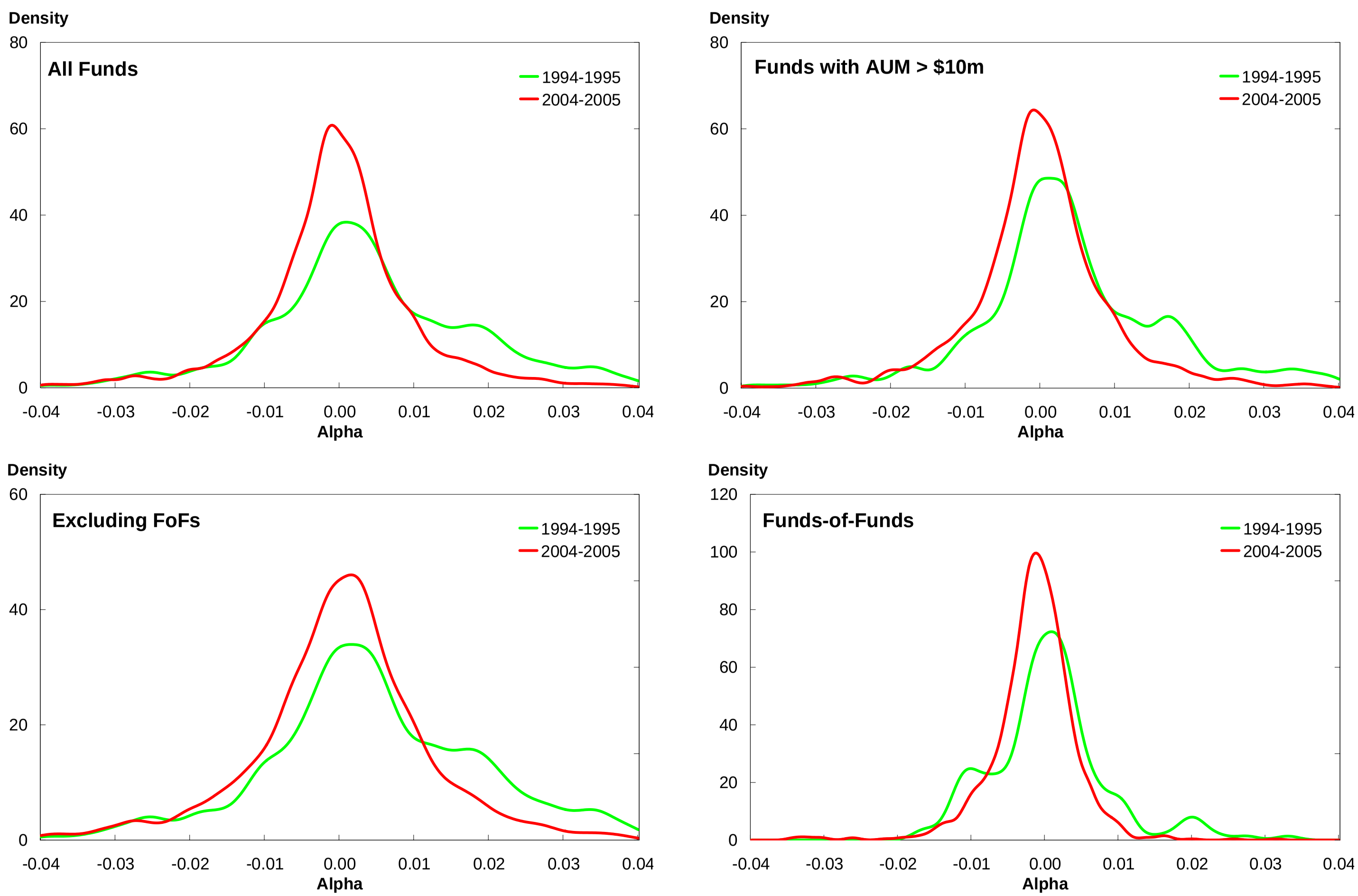

Figure 6.3: Distribution of alpha using alternative sub-sample periods. This figure plots the empirical density functions of individual hedge fund alphas (estimated using the seven-factor model and after controlling for incubation bias) during the first period (1994-1995) and the last period (2004-2005). Four samples are considered: all funds, funds with AUM of more than $10 million, funds that are not funds-of-funds, and funds-of-funds.

Chapter 7

Conclusions

This thesis intends to explain why hedge fund alpha has decreased over the last decade. Using individual hedge fund data, we find a number of interesting results. First, we document that the large right tail of the hedge fund distribution (funds with positive alphas) that was once present has shrunk, while the left tail of the distribution (funds with negative alphas) has remained unchanged over the last decade. Thus, the decrease in average alpha is not due to an increasing percentage of funds with unskilled managers and negative alphas, as suggested by the hedge fund bubble hypothesis. Instead, it is due to a decrease in the proportion of funds capable of producing large positive alphas. Our evidence is consistent with the prediction of the capacity constraint hypothesis.

Second, using quantile regression and counter-factual density analysis, we find that a change in fund characteristics (such as the increasing fund size) combined with a change in market conditions (such as the increasing competition in the hedge fund industry) contributes to the decrease in the proportion of funds with positive alphas.

Third, we find that hedge fund investors chase alpha at the individual fund level; thus, funds with large positive alphas receive more flow than those with negative alphas. This is consistent with the increasing emphasis on alpha by institutional investors who have overtaken wealthy individuals as the primary hedge fund investors.

Fourth, fund-level flow has a positive (negative) impact on a fund's future performance for smaller (larger) funds, while strategy-level flow always has a negative impact on the fund's future performance. In addition, there is significant cross-sectional variation in the impact of capacity constraints on funds using different strategies and on funds with different characteristics.

Our findings indicate that the decline in alpha over time is attributable to capacity constraints that arise both from the unscalability of managers' abilities and from the limited profitable opportunities in the market. Therefore, hedge fund investors should consider the capacity constraints at both fund level and strategy level, before making the decision to "chase" alpha.

Appendix A

Quantile Regression

To appreciate the quantile regression, we consider a random variable Y with a probability distribution function

$$F(y) = Prob(Y \leq y), \tag{A.1}$$

the τth quantile of Y is defined as the inverse function:

$$Q(\tau) = inf\left\{y : F(y) \geq \tau\right\}, \tag{A.2}$$

where $0 < \tau < 1$. A special example is the median ($Q(1/2)$). For a random sample $\{Y_1, \ldots, Y_n\}$ of Y, the sample median ξ is the minimizer of the sum of absolute deviations:

$$\min_{\xi \in R} \sum_{i=1}^{n} \left|Y_i - \xi\right|. \tag{A.3}$$

Similarly, the general τth sample quantile $\xi(\tau)$ (the analogue of $Q(\tau)$) is defined as the solution of the following optimization problem:

$$\min_{\xi \in R} \sum_{i=1}^{n} \rho_\tau(Y_i - \xi), \tag{A.4}$$

where $\rho_\tau(z) = z(\tau - I(z < 0)), 0 < \tau < 1$; and $I(\cdot)$ denotes the indicator function.

Remember that in the OLS framework, the linear conditional mean function $E(Y|X = x) = x^{'}\beta$ is estimated by solving:

$$\hat{\beta} = argmin_{\beta \in R^p} \sum_{i=1}^{n} (Y_i - X_i^{'}\beta)^2. \tag{A.5}$$

Likewise, the linear conditional quantile function, $Q(\tau|X = x) = x^{'}\beta(\tau)$, is estimated by solving:

$$\hat{\beta}(\tau) = argmin_{\beta \in R^p} \sum_{i=1}^{n} \rho_\tau(Y_i - X_i^{'}\beta), \tag{A.6}$$

for any quantile $\tau \in (0, 1)$. In particular, for the case $\tau = 1/2$, we minimize the sum of absolute residuals, and obtain the median regression.

Appendix **B**

Estimation of Counter-factual Density

To understand the counter-factual approach, it is useful to view each individual observation as a vector (y, x, t), which is made up of a variable of interest y, a vector x of individual attributes, and a date t. t will take only two values in the following derivation.

The density of y at time t, $f_t(y)$, can be written as the integral of the density of y conditional on a set of individual attributes and on a date t_y, $f(y|x, t_y)$, over the distribution of individual attributes $F(x|t_x)$ at date t_x:

$$\begin{aligned} f_t(y) &= \int_{x \in \Omega_x} dF\big(y, x|t_{y,x} = t\big) \\ &= \int_{x \in \Omega_x} f\big(y|x, t_y = t\big) dF\big(x|t_x = t\big) \\ &\equiv f\big(y; t_y = t, t_x = t\big) \end{aligned} \tag{B.1}$$

where Ω_x is the domain of definition of the individual attributes.

Our objective is to construct the counter-factual density. For instance, $f(y; t_y = 2000\text{s}, t_x = 1990\text{s})$ represents the density of y that would have prevailed in the 2000s, had the distribution of individual attributes remained as it was in the 1990s.

Under the assumption that the market condition in the 2000s, which is represented by the condition density $f(y|x, t_x = 2000\text{s})$, does not depend on the distribution of attributes, the hypothetical density $f(y; t_y = 2000\text{s}, t_x = 1990\text{s})$ is:

$$\begin{aligned} f(y; t_y = 2000\text{s}, t_x = 1990\text{s}) &= \int f(y|x, t_x = 2000\text{s}) dF(x|t_x = 1990\text{s}) \\ &\equiv \int f(y|x, t_y = 2000\text{s}) \psi_x(x) dF(x|t_x = 2000\text{s}), \end{aligned} \tag{B.2}$$

where the "re-weighting" function $\psi_x(x)$ is defined as:

$$\psi_x(x) \equiv dF(x|t_x = 1990\text{s})/dF(x|t_x = 2000\text{s}). \tag{B.3}$$

Note that the counter-factual density is identical to the kernel density in the 2000s except for the re-weighting function $\psi_x(x)$. If we can obtain an estimate of $\hat{\psi}_x$, then the counter-factual density can be estimated as:

$$\hat{f}(y; t_y = 2000\text{s}, t_x = 1990\text{s},) = \sum_{i \in S_{2000\text{s}}} \frac{\hat{\psi}_x(x_i)}{h} K\left(\frac{y - Y_i}{h}\right), \tag{B.4}$$

where $S_{2000\text{s}}$ is the set of indexes of the 2000s sample.

By applying Bayes' rule, $\psi_x(x) \equiv dF(x|t_x = 1990\text{s})/dF(x|t_x = 2000\text{s})$ can be written as:

$$\psi_x(x) = \frac{Pr(t_x = 1990\text{s}|x)}{Pr(t_x = 2000\text{s}|x)} \cdot \frac{Pr(t_x = 2000\text{s})}{Pr(t_x = 1990\text{s})}. \tag{B.5}$$

The probability of being in period t, given individual attributes x, can be estimated using a probit model:

$$Pr(t_x = t|x) = Pr(\epsilon > -\beta' H(x)) = 1 - \Phi(-\beta' H(x)), \tag{B.6}$$

where $\Phi(\cdot)$ is the cumulative normal distribution, and $H(x)$ is a vector of covariates that is a function of x. The unconditional probability $Pr(t_x = 1990\text{s})$ is equal to the number of observations in 1990s divided by the number of observations in both the 1990s and the 2000s. $Pr(t_x = 2000\text{s})$ is calculated similarly. After obtaining the estimate of $\hat{\psi}_x(x)$, we can estimate the counter-factual density by using equation B-4.

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