The Life Cycle of Hedge Funds: Fund Flows, Size and Performance *

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Abstract

Since the 1980s we have seen a 25% yearly increase in the number of hedge funds, and an annual attrition rate of 7.10% due to liquidation. This paper analyzes the life cycles of hedge funds. Using the TASS database provided by the Tremont Company, it studies industry and fund specific factors that affect the survival probability of hedge funds. The findings show that in general, investors chasing individual fund performance decrease probabilities of hedge funds liquidating. However, if investors follow a category of hedge funds that has performed well, then the probability of hedge funds liquidating in this category increases. We interpret this finding as a result of competition among hedge funds in a category. As competition increases, marginal funds are more likely to be liquidated than funds that deliver superior risk-adjusted returns. We also find that there is a concave relationship between performance and assets under management. The implication of this study is that an optimal asset size can be obtained by balancing out the effects of past returns, fund flows, market impact, competition and favorable category positioning that are modeled in the paper. Hedge funds in illiquid categories are subject to high market impact, have limited investment opportunities, and are more likely to exhibit an optimal size behavior compared to those in more liquid hedge fund categories.

Keywords: Competition; Fund Flows; Hedge Funds; Performance; Optimal Asset Size.

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1 Introduction

The hedge fund industry has grown tremendously since it was founded 50 years ago. Since the late 1980s, the number of hedge funds has risen by more than 25% per year. The value of assets under management has grown as well. In 1990, $39 billion was invested in hedge funds, and in 2003, it was estimated that $650 - $700 billion is managed by 5,000 single-manager hedge funds (Tremont Company). However, alongside the tremendous growth, there has also been a significant attrition in the industry. The annual liquidation rate in the hedge fund industry is 7.10% compared to 1.00% in the mutual fund industry. Despite the increased interest in hedge funds as an asset class, we have only a limited understanding of what drives hedge fund continuation and liquidation. This paper explores the drivers of the life-cycles of hedge funds. Both individual and category [1] related factors are explored in the paper, using the TASS database provided by the Tremont Company.

First, we study the determinants of fund flows. We analyze how net flows into individual funds are affected by past fund performance, current performance, past flows, age, past standard deviation of returns, and past assets. An increase by 10% in a current return increases fund flow by 2%. The relationship between current flow and past return, however, is non-linear. A piecewise linear relationship model between current fund flows and past fund performance is proposed and analyzed. As with private equity funds (Kaplan and Schoar (2003)), the relationship between flows and past returns is positive and concave, so that the top performing funds do not grow proportionally as much as the average fund in the market. An increase in age, assets under management and standard deviation of returns negatively affects fund flows.

Funds flows are also influenced by categories hedge funds belong to. We extend the fund flows-performance analysis to different hedge fund categories. Investors in hedge funds that follow directional strategies, i.e., strategies that follow trends, such as "Global Macro" and "Dedicated Short Seller" are more responsive to past returns. On the other hand, investors in "Market Neutral" and "Event Driven" categories are less responsive to past returns as these categories are more driven by market conditions and events peculiar for that particular

[1] A category is defined as belonging to one of 11 strategies described in Appendix A.2.

time.

Withdrawals due to poor performance can lead to liquidation (Berk and Green (2002) and Vayanos (2003)). Liquidation can appear in two forms: failure of the fund or closure of the fund. Failure can happen due to fraud, forced liquidation due to levered positions that falls below a threshold, or concentrated bets that go against the manager's strategy. Closure can happen if a hedge fund exhausts all opportunities within a category, cannot obtain more capital, or has a bad performance. In the first case, as in bankruptcy, hedge fund managers and investors incur significant costs due to the loss of the capital. In the case of liquidation due to closure, hedge fund investors, rather than managers, incur search costs as they now have to look for new investment opportunities in the hedge fund industry. The new investors might incur higher management and incentive fees in a new fund, as well as being subject to a 2-3 year lock-up period, which is mandatory for new investors. Moreover, liquidation increases survivorship bias which can cause new investors to overestimate potential returns from hedge funds.

Second, this paper studies the determinants of category flows, that is, aggregated fund flows into a category. We find that investors are more likely to invest in categories that have done well. Controlling for fund characteristics, such as returns, age, and assets under management, hedge funds are less likely to be liquidated if they are located in favorable categories. We introduce a favorable positioning metric that determines whether a hedge fund is located in a category that experiences an increased proportional net dollar flow compared to other categories. An increase in the favorable positioning metric decreases the liquidation probability of a hedge fund. However, at the same time, it increases competition due to hedge fund entry into the favorable category. Hedge funds compete for limited opportunities and capital, thus increasing the liquidation probability of a fund. This finding is contrary to what we find by analyzing individual fund flows. As hedge fund investors chase fund returns, thus increasing flows into a fund, the liquidation probability is decreased. However, as hedge fund investors chase category returns, the liquidation probability increases due to competition effects. We also find that as competition increases, marginal funds exit first, and funds that deliver superior returns are left as they are able to withstand competition.

Finally, we look at the relationship between performance and assets under management, both of which affect the life cycles of hedge funds. We find that the relationship between current performance and past asset size is positive and concave. Agarwal, Daniel and Naik (2003), and Goetzmann, Ingersoll, and Ross (2003) find a similar relationship. We confirm this result and extend it to different hedge fund strategies. The performance-asset size relationship takes on different functional forms for different categories. For instance, for illiquid categories such as “Emerging markets” and “Convertible arbitrage” that experience high market impact and are subject to limited opportunities, the relationship is concave and the optimal size can be calculated. The result is opposite for liquid categories such as “Dedicated short bias” and “Equity market neutral” categories. We also propose a model that accounts for fund effects, favorable positioning, competition and market impact. The resulting model produces concave relationship between returns and past assets and an optimal asset size using realistic estimates. The result is important for hedge fund managers and investors because managers of hedge funds with high asset sizes might choose to close the funds to new investors before facing a decrease in returns and an increase in liquidation probabilities. Also, by maximizing returns to hedge fund investors, an optimal asset size can be calculated.

This paper analyzes the effects of fund and category specific factors on life cycles of hedge funds. It introduces new concepts such as competition, favorable positioning and a life cycle in intermediation and hedge fund literatures.

Before describing the empirical analysis of the life cycles in hedge funds, we provide a brief hedge fund overview in Section 2 and a literature review in Section 3. The data are described in Section 4. Performance-fund flow relationship is estimated for different hedge fund styles in Section 5. The effects of category flows, favorable positioning and competition on the liquidation probability of a hedge fund are analyzed in Section 6. The performance-asset size relationship is analyzed in Section 7, and the optimal asset size for different hedge fund categories is calculated. Moreover, a performance model that takes into the account the effects of flows, returns, competition, favorable positioning and market impact is proposed in this section. We conclude in Section 8.

2 Hedge Fund Overview

As of October 2003, the size of the global single-manager hedge fund universe (not including funds of funds) is \$650 - \$700 billion (Tremont Company). There are about 5,000 global single-manager hedge funds in the hedge fund universe. There are about 1,200 - 1,400 funds of funds. There are about 3,000 distinct hedge fund managers that manage both offshore and domestic accounts. In 1990, there were 610 funds managing \$39 billion. Hedge funds differ from mutual funds and other investment vehicles by both internal structure and investment discipline. Hedge fund managers are not restricted to any particular type of investments. Hedge funds can buy (long) or sell (short) securities that they do not own. They are not restricted to common "buy and hold" strategies. Most U.S. hedge funds are limited partnerships, or limited liability companies, established to invest in public securities. However, there is no common definition of a hedge fund. U.S. hedge funds are defined by their freedom from regulatory controls stipulated by the Investment Company Act of 1940. Before 1996, a hedge fund had a 100 investor limit in order to qualify as a limited partnership. However, under the National Securities Markets Improvement Act of 1996, the 100 investor limit was lifted. The minimum new worth requirement for a qualified investor is \$5 million and the minimum institution capital is \$25 million. Companies can also become reporting companies voluntarily by filing with the SEC. Under the Exchange Act, a company must become a reporting company if it has at least 500 shareholders and \$10 million in assets. The Exchange Act contains registration and reporting provisions that may apply to hedge funds.

Depending upon their activities, in addition to complying with the federal securities laws, hedge funds and their advisers may have to comply with other laws including the Commodity Exchange Act ("CEA"), rules promulgated by the National Association of Securities Dealers ("NASD") and/or provisions of the Employment Retirement Income Security Act ("ERISA"). In addition, hedge funds may be subject to certain regulations promulgated by the Department of the Treasury, including rules relating to the prevention of money laundering. Moreover, hedge fund advisers are subject to certain state laws.

Offshore hedge funds are typically corporations registered in a tax haven such as the

British Virgin Islands, the Bahamas, Bermuda, the Cayman Islands, Dublin, or Luxembourg, where tax liabilities to non-U.S. citizens are minimal. In general, the hedge fund industry is not transparent to regulators unlike the mutual funds industry. Like mutual funds, hedge funds are actively managed investment portfolios holding positions in publicly traded securities. However, unlike mutual funds, hedge funds have greater flexibility in the kind of securities they can invest in. Hedge funds can invest in domestic and international debt and derivative securities. They can take undiversified positions, sell short, and lever up their portfolios. These alternative investments mainly attract institutions and wealthy individuals with minimum investments typically in the range of $250,000 - $1 million. Hedge funds are also characterized by a substantial managerial investment and strong managerial incentives. On average, hedge fund managers receive a 1% annual management fee and 20% of the annual profits. Most of funds employ a bonus incentive fee: managers are paid a percentage of the excess of a fund's return over some level, commonly called a "high-water mark." If a hedge fund incurred losses in the past, its managers can be paid in present period only if return in this period exceeds the "high-water mark" plus past losses.

3 Literature Review

Given the availability of public and private hedge fund databases such as TASS, AltVest, Hedge Fund Research (HFR) and Managed Account Reports (MAR), numerous studies have analyzed hedge fund performance. For example, Ackermann, McEnally and Ravenscraft (1999), Agarwal and Naik (2000b, 2000c), Edwards and Caglayan (2001), Fung and Hsieh (1999, 2000, 2001), Kao (2002), and Liang (1999, 2000, 2001) provide empirical studies of hedge fund performance using different hedge fund databases. In comparison, Brown, Harlow and Starks (1996), Chen, Hong, Huang and Kubik (2003), and Chevalier and Ellison (1997) provide empirical performance analysis studies for mutual funds; Kaplan and Schoar (2003) do so for private equity funds.

Performance attribution and style analysis in hedge funds have been studied in the following papers: Agarwal and Naik (2000), Brown and Goetzmann (2001), Brown, Goetzmann and Ibbotson (1999), Brown, Goetzmann, and Park (1997, 2000, 2001), Fung and Hsieh

(1997), and Lochoff (2002). Ackermann et al. (1999) and Brown, Goetzmann, Ibbotson, and Ross (1992) find that hedge fund databases can suffer from survivorship biases that can bias both first and second moments in returns. According to Ackermann et al. (1999), termination and self-selection biases are the most powerful data-conditioning biases. Funds that are closed leave the database due to termination. Funds that choose not to be included in the database can voluntarily withdraw from databases. Performance studies of existing hedge funds may be artificially inflated if poorly performing funds are systematically omitted from the database. Brown, Goetzmann and Ibbotson (1999) find that the survivorship bias is about 3 percentage points per year for offshore hedge funds.

Favorable category positioning and competition have not been introduced in the hedge fund literature, and their effects on the life cycles of hedge funds have not been studied. In the Industrial Organization literature, authors find that an increase in competition leads to an increase in the probability of liquidation in a firm (Aghion, Dewatripont and Rey (1995) and Schmidt (1997)). The life cycle of a firm is studied by Mueller (1972).

Khorana and Servaes (1999) find that mutual fund starts are positively related to the level of assets invested in and capital gains embedded in other funds with the same objective. For mutual funds, Chen, Hong, Huang, and Kubik (2003) find that controlling for its size, a fund's performance increases with the asset base increase of other funds in the family that the fund belongs to. For private equity funds, Kaplan and Schoar (2003) find that in the periods of an overall increased entry of funds into the industry, there is a large negative effect on the performance of younger funds compared to the performance of older, more established funds. Unlike mutual funds and private equity funds, hedge funds have very distinct categories with a high barrier to entry. It takes time and managerial talent to set up a hedge fund in a particular category. Therefore, empirical analysis of the effect of favorable positioning of a category and competition among hedge funds within a category can provide insights into understanding the life cycles of hedge funds.

Hedge funds that have higher returns experience higher net flows. Agarwal, Daniel, and Naik (2003) find a convex relationship in hedge fund flow-performance relationship. Ippolito (1992), Chevalier and Ellison (1997), Goetzmann and Peles (1997), Gruber (1996), Sirri and Tufano (1998) and Zheng (1999) look at the determinants of money flows in mutual funds, and find a positive and convex relationship. However, Kaplan and Schoar (2003) find a concave relationship for private equity funds.

The impact of volatility on fund net flows is modeled theoretically by Vayanos (2003) and studied empirically for mutual funds by Chevalier and Ellison (1997). They find that the higher volatility leads to more outflows.

Withdrawals due to poor performance can lead to liquidation (Berk and Green (2002) and Vayanos (2003)). Amin and Kat (2002), Bares, Gibson and Gyger (2001), Brown, Goetzmann and Ibbotson (1999), Brown, Goetzmann and Park (2001), Fung and Hsieh (2000), Gregoriou (2002), and Liang (2000, 2001) focus on hedge fund survival rates. Baquero, Horst, and Verbeek (2002) look at liquidation probabilities of individual hedge funds and find that they are greatly dependent on past performance.

Agarwal, Daniel, and Naik (2003) and Goetzmann, Ingersoll and Ross (2003) find decreasing returns to scale in hedge funds. Perold and Salomon (1991) report decreasing returns to scale in mutual funds and propose an optimal size calculation for mutual funds. Kaplan and Schoar (2003) find decreasing returns to scale in the private equity industry. Our paper suggests that an optimal size can be calculated for different hedge fund categories.

4 Data Description

The TASS database is used for the empirical analysis. As of 2003, the TASS database tracks $270 billion held by global single-manager hedge funds and $63 billion held by funds of funds. These numbers exclude money held in separately managed accounts. There are other databases like AltVest, Hedge Fund Research (HFR) and Zurich Capital Markets/Managed Accounts Reports (ZCM/MAR). However, the TASS database is the most comprehensive one. The TASS database consists of 3,928 hedge funds from November 1977 to April 2003.[2] The database is divided into two parts: "Live" and "Graveyard" funds. Funds that are in the "Live" category are considered to be active as of April 2003. Once a hedge fund is considered no longer active, it is transferred into the "Graveyard" category. Hedge funds are in the "Graveyard" category if they stop reporting their performance, are liquidated,

[2] For further information about the TASS database, see http://www.tassresearch.com.

closed to new investment, restructured, or merged with other hedge funds. A hedge fund can be listed in the "Graveyard" database only after being listed in the "Live" database. However, the TASS database is subject to backfill bias: When a fund decides to be listed in the database, all its prior history is incorporated in the TASS database. Also, due to reporting delays, some "Graveyard" funds can be incorrectly listed in the "Live" database. Tremont adopted a policy of transferring funds from the "Live" to the "Graveyard" database if its managers have not heard from hedge funds or were not able to contact the hedge fund managers over a 6-8 month period. Because the "Graveyard" database became active in 1994, thus funds that were dropped from the "Live" database before 1994 were not recorded by TASS, the database is subject to some degree of survivorship bias.[3]

For the analysis in this paper, another sub-database, called "Liquidated" is constructed. This sub-database has funds that are liquidated. To construct the sub-database, we eliminate funds from the "Graveyard" category that are there due to mergers with other hedge funds, that are dormant, or that decided not to list in the database due to their large size. Moreover, we eliminate funds that decided to be closed to new investment, and therefore, not needing advertisement by being listed in the database, got matured, or got reconstructed. In order to compile the "Liquidated" sub-database, we carefully examined the "Notes" section provided by TASS to understand the history of each hedge fund, researched the history of funds, and talked to TASS employees who communicate directly with hedge fund managers. Most hedge funds in the "Graveyard" category with less than $20 million in assets on the last day that the funds were reported are actually liquidated and therefore we put them in the "Liquidated" sub-database. The exception is the funds that merged. There are some hedge funds in the TASS database that stopped reporting their performance to the Tremont between September 2002 and April 2003 and have less than $20 million of assets on the last reporting date. These funds might have characteristics of funds that are liquidated - low returns, and very low assets under management (less than $20 million). However, they are not considered in the "Liquidated" database due to reporting delays. TASS allows up to 8

[3] For studies attempting to quantify the degree and impact of survivorship bias, see Brown, Goetzmann, Ibbotson, and Ross (1992), Brown, Goetzmann, and Ibbotson (1999), Brown, Goetzmann, and Park (1997), Carpenter and Lynch (1999) and Fung and Hsieh (1997b, 2000).

months delay before further investigation and before considering the hedge fund a liquidation, unless, during this 8 month period, it is discovered that the hedge fund is liquidated.

The database is further filtered by considering only hedge funds that report monthly and net-of-fees returns. Hedge funds for which monthly returns or monthly assets are missing are eliminated. Also, to correct for the termination bias, the data from January 1994 until December 2002 is used. In the end, the "Combined" database contains 3,501 hedge funds with continuous net-of-fees monthly returns and monthly assets under management. Out of 3,501, 1,264 funds are in the "Liquidated" sub-database, and 2,237 funds are in the "Successful" subcategory, representing funds still alive. There are 1,387 hedge funds in the "Graveyard" database, out of which 1,264, or 91% are failures; the rest decided not to advertise through TASS, decided to be closed to new investment, or merged with other hedge funds.

The TASS database considers 11 different investment style categories, described in detail in Appendix A.2. The number of hedge funds in each category is presented in Table A.1.

[INSERT TABLE A.1]

The dynamics of annual hedge fund entries and exits are presented in Table A.2. As of 1994, the date when the TASS database started reporting hedge fund liquidations, the average annual attrition rate has been 7.33%. The average attrition rate due only to liquidation is 7.10%.

[INSERT TABLE A.2]

Summary statistics for monthly returns, standard deviation of monthly returns, age, assets under management as well as favorable category positioning and competition metrics for both hedge funds and fund of funds are presented in Table A.3.

[INSERT TABLE A.3]

5 Performance-Fund Flow Relationship

Berk and Green (2002) and Vayanos (2003)propose theoretical models in which fund specific factors such as flows and returns affect liquidation probabilities. This section presents an empirical analysis of the effects of fund specific factors on liquidation probabilities. Also, the fund specific factors are correlated. For example, current fund flows depend on past returns (Agarwal, Daniel and Naik (2003)). The authors find that the relationship between fund flows and performance is positive and non-linear in past performance.

5.1 Hypotheses

Hypothesis 1: As investors chase high fund returns, the liquidation probability of the hedge fund decreases.

5.2 Methodology

The performance-fund flow function is estimated using a piecewise linear relationship between current flows and past returns. A modified methodology proposed by Sirri and Tufano (1998) to study performance fund flow relationship in mutual funds is used. Fractional rank terciles, $Trank_{i,t-1}$ for each time t and fund i are constructed. First, a fractional rank, F_{rank}, is calculated for each fund, from 0 to 1 based on returns in year t-1. Then, $Trank^1$, the bottom tercile rank, $Trank^2$, the middle tercile rank and $Trank^3$, the top tercile rank are calculated as follows: $Trank^1$=$Min(\frac{1}{3}$, $F_{rank})$,
$Trank^2$=$Min(\frac{1}{3}$, F_{rank}-$Trank^1)$,
$Trank^3$=$Min(\frac{1}{3}$, F_{rank}-$Trank^1$-$Trank^2)$,

The following regression is specified to understand the determinants of fund flows:

$$
\begin{aligned}
Flow_{i,t} = \alpha_{i,t} + \sum_{j=1}^{3} \beta_1^j (Trank_{i,t-1}^j) + \beta_2 Size_{i,t-1} + \beta_3 Age_{i,t-1} \\
+ \beta_4 Flow_{i,t-1} + \beta_5 Return_{i,t} + \beta_6 \sigma_{i,t-1} \\
+ \sum_{k=1}^{10} \beta_7^c I(Category_{i,k}) + \epsilon_{i,t}
\end{aligned}
\tag{1}
$$

Current quarterly flows are regressed on bottom, middle and top terciles of last quarter performance, current fund return, last quarter flow, last quarter asset size, age, and the last quarter standard deviation of returns. The quarterly data from 1994 until 2002 is used.

Empirical studies define net flow of funds as a percentage change in new assets adjusted for return.

$$
F_t = \frac{A_t - A_{t-1}(1 + r_t)}{A_{t-1}} \tag{2}
$$

However, this measure downplays the significance of very large negative returns that lead to a hedge fund liquidation. If a hedge fund is liquidated at time t, then, A_t is 0, and $\frac{A_t - A_{t-1}(1+r_t)}{A_{t-1}} = -(1 + r_t)$. Therefore, when a fund is liquidated, the minimum return will be $r_t = -1$ or -100%. Under the conventional metric of measuring the flow, the response to the flow is 0. Therefore, to correct for this, in the empirical analysis, the flow measure is set to -1 when a fund is liquidated.

To test Hypothesis 1 whether an increase in returns and flows impacts liquidation probabilities of hedge funds, we specify the following logit model.

$$
\begin{aligned}
Liquidation_{i,t} = f(\alpha_{i,t} + \beta_1 Age_{i,t} + \beta_2 r_{i,t-1} \\
+\beta_3 r_{i,t} + \beta_4 Flow_{i,t-1} + \beta_5 Assets_{i,t-1} \\
+\sum_{k=1}^{10} \beta_6^c I(Category_{i,k}) + \sum_{t=1}^{38} \beta_7^t I(Time_{i,t}) + \epsilon_{i,t})
\end{aligned}
\tag{3}
$$

5.3 Results

We find that average net flows into funds in different terciles are as follows: Top: 42.15%, Medium: 5.68%, Bottom: -21.62% per quarter. As predicted, higher returns lead to higher future flows.

The Fama-MacBeth results for the piecewise linear relationship between current flows and past returns are presented in Table A.4.

[INSERT TABLE A.4]

Better performing funds are more likely to attract funds than poorly performing funds. This relationship is concave so that the top performing funds do not grow proportionally as much as the average fund in the market. Top funds might choose not to grow that fast in order not to face diminishing returns. For the analysis of the regions of diminishing returns, see Section 7. The relationship is concave for private equity funds as well (Kaplan and Schoar (2003)). In the mutual fund literature, the relationship is convex, so that the top performing funds increase their share of the overall hedge fund market (Sirri and Tufano (1998)).

For the bottom tercile, the estimate is 0.293 with a t-stat of 5.46. For the middle tercile, the estimate is 0.269 with a t-stat of 5.46. For the top tercile, the estimate is 0.006 with a t-stat of 0.08. Therefore, if in the last quarter a hedge fund was in a top tercile, an increase of return by 10% would lead to a 0.8% increase in flows, and if the hedge fund was in a bottom tercile, an increase of return by 10% would lead to 2.9% increase in flows. In contrast, Agarwal, Daniel and Naik (2003) find that the fund flow-performance relationship is convex for hedge funds. However, unlike this paper, the authors use data from 1994-2000. They also look only at the annual relationship between flows and returns. We find that there is a high degree of volatility in flows and returns on an annual basis. That is why we look at the quarterly data. Also, the authors use the combination of HFR, TASS, ZCM/MAR databases, and we use only the TASS database. The relationship between current returns and current flows is positive and significant with a coefficient of 0.234. Past flows positively affect current flows with a coefficient of 0.048. However, both past size and age negatively affect the future flows with coefficients of -0.041 and -0.001, respectively. Asset size is measured as a natural logarithm of assets under management. The topic of an asset size and the notion of an optimal asset size are covered thoroughly in Section 7. The past standard deviation of returns negatively affects current quarterly flows with a coefficient of -0.002. People are less likely to invest or hold their money in a hedge fund with high volatility, after adjusting for returns. The R^2 for the regression is 5.53%.

To understand whether there are any category effects on the performance-fund flow relationship, we estimate the same model for each fund category and present results in Table A.5.

[INSERT TABLE A.5]

For all categories, the fund flow-performance relationship is positive and concave. By looking at the middle coefficient of past returns, $Trank^2$, we study the average impact of past returns on current flows for different hedge fund categories. We expect that hedge funds that have more directional focus by concentrating on trends have a higher impact of past returns on flows. Funds that follow event oriented and market timing strategies should have a lower impact of past returns on flows. The expectations are closely correlated with the data depicted in Table A.6.

[INSERT TABLE A.6]

Hedge fund categories that have more of a directional focus like "Dedicated Short Bias," "Fixed Income Arbitrage," "Global Macro," "Long/Short Equity" and "Managed Futures" have higher estimates of $Trank^2$. More event oriented strategies and less directional strategies such as "Convertible Arbitrage," "Emerging Markets," "Event Driven" and "Equity Market Neutral" have much smaller coefficients.

To test Hypothesis 1, whether an increase in returns and flows affects liquidation probability of hedge funds, the logit model is specified in equation 3. The results are depicted in Table A.7.

[INSERT TABLE A.7]

The implied probability of liquidation is 0.60% per quarter.

We also adjust coefficients by the mean in the logistic specification so it is possible to directly compare the effects of each coefficient on the liquidation probability. The results are depicted in Table A.8.

[INSERT TABLE A.8]

Both current and past returns and past flows negatively affect liquidation probability. Past asset size also negatively impacts the liquidation probability and has the biggest effect for each percentage deviation from the mean.

Results of the likelihood ratio test and the efficient score test for testing the joint significance of the explanatory variables are included in Table A.9.

[INSERT TABLE A.9]

6 Favorable Positioning and Competition

Different fund characteristics such as fund returns, flows, asset size and age affect the liquidation of hedge funds. Returns are affected by abilities of fund managers, costs, and exogenous shocks to hedge fund investment portfolios. However, even if a manager is able to deliver solid returns, a fund can still be liquidated due to other factors. We propose that given a fund manager's abilities and other fund characteristics, a hedge fund's probability to survive is affected by favorable positioning and competition. The paper is the first to introduce the concepts in the literature on financial intermediation and asset pricing. Competition and its effects on liquidation probability are introduced in the Industrial Organization literature (Aghion, Dewatripont and Ray (1995) and Schmidt (1997)).

A hedge fund experiences favorable positioning if it is located in the right category at the right time. This category experiences a higher proportional increase in net dollar fund flows compared to other categories. A hedge fund experiences competition if it is surrounded by a lot of funds in its category. However, the relationship among favorable positioning, competition, and the probability of liquidation is not obvious and provides surprising results and insights into understanding the life cycles of hedge funds.

Below we list examples of hedge funds in the database that are liquidated even though the returns at the time of liquidation are positive for each of the funds. The liquidation is affected by high competition, low favorable positioning, or both.

Reference 10. Category: Long/Short Equity. The fund is liquidated in March 1999. The return at the time of liquidation was 3.87%. The flow a quarter before the liquidation was -78.96%. The average monthly return during the past year was -0.01%. The favorable positioning metric (FAV) in Q4, 1998 was -0.24. The number of competitors in Q4, 1998 was 497.

Reference 15. Category: Long/Short Equity. The fund is liquidated in April 1995. The return at the time of liquidation was 2.17%. The flow a quarter before the liquidation was 3.20%. The average monthly return during the past year was 0.57%. The favorable positioning metric (FAV) in Q1, 1995 was -0.21. The number of competitors in Q1, 1995 was 192.

Reference 4429. Category: Long/Short Equity. The fund is liquidated in January 2001. The return at the time of liquidation was 31.40%. The flow a quarter before the liquidation was 29.99%. The average monthly return during the past year was 6.93%. The favorable positioning metric (FAV) in Q4, 2000 was 0.2910. The number of competitors in Q4, 2000 was 693.

Reference 560. Category: Managed Futures. The fund is liquidated in December 1995. The return at the time of liquidation was 8.21%. The flow a quarter before the liquidation was 0%. The average monthly return during the past year was -0.40%. The favorable positioning metric (FAV) in Q3, 1995 was -0.05. The number of competitors in Q3, 1995 was 211.

Reference 563. Category: Managed Futures. The fund is liquidated in December 1995. The return at the time of liquidation was 2.16%. The flow a quarter before the liquidation was 3.20%. The average monthly return during the past year was 1.13%. The favorable positioning metric (FAV) in Q3, 1995 was -0.05. The number of competitors in Q3, 1995 was 211.

6.1 Hypotheses

Hypothesis 2: As investors chase category returns, they move money into the favorable category. The favorable category that experiences a higher proportional increase in net dollar fund flows compared to other categories, attracts other hedge funds into the category, thus increasing the liquidation probability of hedge funds in that category. Therefore, as investors chase category returns, by investing in a favorable category, the liquidation probability of hedge funds in that category increases due to competition effects.

Hypothesis 3: As the competitors become smaller, measured by asset value, their impact on liquidation probability reduces.

Hypothesis 4: As competition within a strategy increases, marginal performers leave and only hedge funds with superior risk-adjusted performance survive.

6.2 Methodology

To test Hypothesis 2, we define a Favorable Positioning metric (FAV). FAV measures whether a fund category experiences a higher proportional increase in net dollar fund flows compared to other categories. Hypothesis 2 proposes that if a hedge fund is in the right category at the right time, in other words, in the category with high FAV value, then the liquidation probability of the hedge fund decreases. However, increased FAV leads to an increase in competition which increases the liquidation probability.

In order to define FAV, we need to define fund Dollar Flow at any time t.

$$DollarFlow_{i,t} = A_{i,t} - A_{i,t-1}(1 + r_{i,t}) \tag{4}$$

Equation 4 assumes that fund flows occur at the end of the month, which is true for hedge funds. If an investor chooses to deposit or withdraw money into a hedge fund, he usually has to wait until the end of the month to make the transaction. Of course, for new investors, the average lock-up period is 2 years, which limits the outflow of money from a hedge fund.

Dollar Flows are then aggregated over a quarter to calculate the Quarterly Dollar Flow. Then, as in Chevalier and Ellison (1997), Sirri and Tufano (1998) and Agarwal, Daniel, and Naik (2003), quarterly dollar flows are scaled by the beginning-of-quarter assets under management to measure flows. Flows capture the change in size due to net money flows.

$$Flow_{i,t} = \frac{QuarterDollarFlow_{i,t}}{A_{i,t-1}} \tag{5}$$

FAV is a favorable positioning metric that is measured as follows:

$$FAV_{k,t} = \frac{\sum_{i,i \in k} QuarterDollarFlow_{i,t}}{\sum_{i,i \in POSNET} QuarterDollarFlow_{i,t}} \tag{6}$$

If category k experiences net positive flows during the quarter. POSNET is a set of category flows that are net positive during the quarter.

$$FAV_{k,t} = -\frac{\sum_{i,i \in k} QuarterDollarFlow_{i,t}}{\sum_{i,i \in NEGNET} QuarterDollarFlow_{i,t}} \tag{7}$$

If category k experiences net negative flows during the quarter. NEGNET is a set of category flows that are net negative during the quarter. By construction, FAV metric lies between -1 and 1.

To test whether FAV is affected by previous category return, we run the following regression model:

$$FAV_{k,t} = \alpha_{k,t} + \beta_1 r_{k,t-1} + \epsilon_{k,t} \tag{8}$$

To test the relationship between liquidation probability and FAV, we run the logit model of the probability of liquidation on current age, return during the past quarter, return during the current quarter, past quarter flow, past quarter FAV, and past quarter assets measured as the natural logarithm of assets under management. The model controls for category and time effects.

$$\begin{aligned} Liquidation_{i,t} = f(\alpha_{i,t} + \beta_1 Age_{i,t} + \beta_2 r_{i,t-1} \\ + \beta_3 r_{i,t} + \beta_4 FAV_{k,t-1} + \beta_5 Assets_{i,t-1} \\ + \sum_{k=1}^{10} \beta_6^c I(Category_{i,k}) + \sum_{t=1}^{38} \beta_7^t I(Time_{i,t}) + \epsilon_{i,t}) \end{aligned} \tag{9}$$

To make sure that we are not capturing a trend in variables, the FAV metric is graphed for each category over time, and no consistency in the behavior is found.

EntryFraction for a category k at time t is defined as follows:

$$EntryFraction_{k,t} = \frac{ENTRY_{k,t}}{NUMBER_{k,t-1}} \tag{10}$$

where $ENTRY_{k,t}$ is the number of funds entering a particular category k in a quarter t and $NUMBER_{k,t-1}$ is the number of funds in the category at the end of the quarter t-1.

To measure the effect of FAV on EntryFraction, the following regression is performed:

$$EntryFraction_{k,t} = \alpha_{k,t} + \beta_1 FAV_{k,t-1} + \epsilon_{k,t} \tag{11}$$

However, it takes time for hedge fund managers to perceive the "hotness" of the category as well as to set-up a fund. Therefore, we perform the similar regression on 4 lags of FAV (up to a year).

$$EntryFraction_{k,t} = \alpha_{k,t} + \beta_1 FAV_{k,t-1} + \beta_2 FAV_{k,t-2} + \beta_3 FAV_{k,t-3} + \beta_4 FAV_{k,t-4} + \epsilon_{k,t} \quad (12)$$

To understand the relationship between competition and liquidation probability, we run the logit model of the probability of a hedge fund liquidation on current age, return during the past quarter, return during the current quarter, past quarter flow, the number of hedge funds in the category a year before, and past quarter assets measured as the natural logarithm of assets under management. The model is controlled for category and time effects. The number of hedge funds in the category is a proxy for competition. The reason why a year lag is taken when calculating competition is because it takes some time for hedge funds to enter a category and become competitive. They need to raise awareness in the hedge fund community, communicate their strategy to new investors, build relationships with dealers and bankers who extend credit, and build a track record to attract new investors.

$$\begin{aligned} Liquidation_{i,t} = f(&\alpha_{i,t} + \beta_1 Age_{i,t} + \beta_2 r_{i,t-1} \\ &+\beta_3 r_{i,t} + \beta_4 Number_{k,t-4} + \beta_5 Assets_{i,t-1} \\ &+\sum_{k=1}^{10} \beta_6^c I(Category_{i,k}) + \sum_{t=1}^{31} \beta_7^t I(Time_{i,t}) + \epsilon_{i,t}) \end{aligned} \quad (13)$$

The data used in the paper is from 1994 until 2002. The TASS started reporting exits by hedge funds starting in 1994. Therefore, during this time period, FAV and competition metrics are going to be correctly calculated.

To test Hypothesis 2, the joint effect of competition and favorable positioning on liquidation probability is modeled. Also, the estimates are controlled for the mean to allow for direct comparison.

$$
\begin{aligned}
Liquidation_{i,t} &= f(\alpha_{i,t} + \beta_1 Age_{i,t} + \beta_2 r_{i,t-1} \\
+\beta_3 r_{i,t} + \beta_4 Number_{k,t-4} + \beta_5 FAV_{i,t-1} &+ \beta_6 Assets_{i,t-1} \\
+\sum_{k=1}^{10} \beta_7^c I(Category_{i,k}) + \sum_{t=1}^{31} \beta_8^t I(Time_{i,t}) &+ \epsilon_{i,t})
\end{aligned}
\tag{14}
$$

To test Hypothesis 3, we run the logit model for liquidation of hedge funds on age, previous return, current return, previous assets measured in logarithmic quantities, previous FRAC, and previous assets under management measured in logarithmic quantities, where FRAC is defined as follows:

$$
Frac_{k,t} = \frac{Number_{k,t}}{\sum_{i,i \in k} Assets_{i,t}} \tag{15}
$$

FRAC measures the fraction of the number of competitors in a category to the overall asset size in the category.

The logit specification is as follows:

$$
\begin{aligned}
Liquidation_{i,t} &= f(\alpha_{i,t} + \beta_1 Age_{i,t} + \beta_2 r_{i,t-1} \\
+\beta_3 r_{i,t} + \beta_4 Number_{k,t-1} + \beta_5 FRAC_{k,t-1} &+ \beta_6 Assets_{i,t-1} \\
+\sum_{k=1}^{10} \beta_7^c I(Category_{i,k}) + \sum_{t=1}^{38} \beta_8^t I(Time_{i,t}) &+ \epsilon_{i,t})
\end{aligned}
\tag{16}
$$

To test Hypothesis 4, we divide competition metric, NUMBER, into 5 quintiles and run the logistic model in equation 14 five times for each of the quintilies.

6.3 Results

Results for Hypothesis 2

The Fama-MacBeth results of the regression model 8 are presented in Table A.10.

[INSERT TABLE A.10]

When pooled regression is used, the coefficient in front of current FAV is 3.347 with a t-stat of 2.93. When the Fama-MacBeth method is used, the coefficient is 1.358 with a t-stat of 1.85. As can be seen, current FAV significantly depends on a previous category return. Investors chase hedge funds in a category that performed well. The R^2 for the regression is 28.46%. Returns are value-weighted.

The results of logit regression specified in equation 9 are presented in Table A.11. Even if a hedge fund manager has skills and a good track record, the hedge fund can still fail simply due to its belonging to the wrong category at the wrong time.

[INSERT TABLE A.11]

For robustness, the FAV metric is plotted over time for each category to make sure that there is no consistent trend in the measure that can diminish the favorable positioning explanation. FAV for each category is plotted over time in the Figure A.1. According to the figure, FAVs for Global Macro and Long/Short Equity are negatively correlated.

[INSERT FIGURE A.1]

The R^2 for the regression is 13.24%. As predicted, the funds with higher current and past returns have a higher survival probability. Funds with higher assets are less likely to fail. Higher FAV leads to lower liquidation probability. The coefficient in front of the FAV measure is -0.502 and is significant at 1% level. Therefore, for a hedge fund, being in the right category at the right time helps to reduce liquidation probability. Given equation 9, the implied probability of liquidation for a particular hedge fund in any quarter is 0.52%. Changing FAV from -1 standard deviation to +1 standard deviation affects the implied probability by -30.11%. [4]

Results of the likelihood ratio test and the efficient score test for testing the joint significance of the explanatory variables are included in the Table A.12.

[INSERT TABLE A.12]

The result shows that a hedge fund is likely to survive if it is in the right category at the right time. If the category as a whole experiences higher inflows than other categories, a hedge fund in this favorable category has a greater probability of survival after controlling for current and past returns, age, and assets under management in the fund.

However, as the category becomes favorable, other hedge funds are more likely to enter into the same category. The barrier of entry to the hedge fund industry is very low, and over time the cost and time of setting up a new hedge fund has greatly diminished.

The proposition is tested in the equation 11 and the results are as follows. The parameter estimate of the $FAV_{k,t-1}$ is 0.018 with t-statistic of 2.24. Therefore, hedge funds tend to be formed in categories which have increased relative net flows.

It takes time for hedge fund managers to perceive the "hotness" of a category as well as to set-up a fund in this favorable category. Therefore, the EntryFraction is regressed on 4 lags of FAV (up to 1 year). The sum of parameter estimates for all 4 lags is 0.038. The R^2 for the regression is 2.15%.

As EntryFraction into a category increases, competition among hedge funds in a category increases. Table A.13 presents results of the following: logit regression of liquidation probability of a hedge fund at time t on intercept, current age, previous quarterly return on investments, current quarterly return, the number of hedge funds in a particular category in the previous year, and previous quarterly assets under management. Even if a hedge fund manager has skills and a good track record, the hedge fund can still fail due to competition among other hedge funds in a category.

[INSERT TABLE A.13]

[4] Implied Probability=$\frac{exp(\alpha_{i,t}+\sum_{z=1}^{n}\beta_{i,t,z}\mu_{i,t,z})}{1+exp(\alpha_{i,t,z}+\sum_{z=1}^{n}\beta_{i,t,z}\mu_{i,t,z})}$ where $\mu_{i,t,z}$ is a mean value for an independent variable z.

The R^2 for the regression is 12.30%. As suggested by Hypothesis 2, a higher number of hedge funds in a category leads to more competition, thus increasing the liquidation probability. The coefficient on the Number is 0.002 and is significant at 1% level. Therefore, competition increases the liquidation probability. Given equation 13, the implied probability of liquidating a particular hedge fund in any quarter is 0.90%. Changing the number of hedge funds in a category from -1 standard deviation to +1 standard deviation increases the implied probability by +76.97%.

Results of the likelihood ratio test and the efficient score test for testing the joint significance of the explanatory variables are included in Table A.14.

[INSERT TABLE A.14]

The results that show the combined effect of competition and favorable positioning are in Table A.15.

[INSERT TABLE A.15]

The results that show estimates adjusted for the mean are in Table A.16.

[INSERT TABLE A.16]

Results of the likelihood ratio test and the efficient score test for testing the joint significance of the explanatory variables in Tables A.15 and A.16 are included in the Table A.17.

[INSERT TABLE A.17]

If FAV and competition are taken into account, then the annual implied liquidation probability of any hedge fund is 2.72%. If these variables are not taken into the account, then the implied liquidation probability is 1.84%.

Overall, hedge funds are likely to survive if they are in the right category at the right time, even after adjusting for performance. If the category falls out of favor, hedge funds have bigger liquidation probability. Hedge funds are not able to raise new capital and withdrawals can lead to forced liquidation due to levered positions that fall below a threshold. If a category has a favorable positioning, it has a positive effect on survival probability as well as on the number of new hedge fund entrants into the favored category. The increase in the competition among the funds in a category leads to an increased proportional liquidation within the hedge fund category.

The quarterly Spearman correlation coefficients for the current liquidation probability, current age, current returns, past returns, past flows, past FAV, the last year's number of hedge funds in a category and past assets are presented in Table A.18. In Spearman correlation only the order of the data is important, not the level, therefore extreme variations in expression values have less control over the correlation, unlike in the Pearson correlation.

[INSERT TABLE A.18]

The correlation between past returns and current flows is positive and significant: 0.211 for quarterly data. The relationship between flows and returns is thoroughly analyzed in the Section 5.

Results for Hypothesis 3

The results of logistic regression specified in 16 are presented in Table A.19.

[INSERT TABLE A.19]

The coefficient in front of the competition metric, NUMBER, is 0.019, positive and significant. Coefficient in front of FRAC is -0.660, negative and significant. Therefore, as competition increases in a particular category k, more hedge funds in that category are likely to be liquidated. However, as more hedge funds control smaller amounts of assets, it improves success probabilities of hedge funds. Competition from smaller hedge funds is less likely to increase liquidation probabilities than competition from bigger hedge funds. This is consistent with Hypothesis 3.

Results for Hypothesis 4

To test Hypothesis 4, we divide competition metric, NUMBER, into 5 quintiles and run the logistic model in equation 14 five times for each of the quintiles. The results for the effect of the past return on liquidation probabilities are depicted in Table A.20. As can be seen from the table, as competition increases, the effect of the past quarterly return on liquidation probabilities increases.

[INSERT TABLE A.20]

As competition within a strategy increases, more hedge funds are looking for diminishing opportunities, compete for scarce capital and leverage opportunities. Marginal funds that deliver average or below average returns are more affected during the increased competition and will be forced to liquidate. Only hedge funds that can deliver superior returns to their investors stay.

7 Optimal Asset Size

Both performance and assets under management impact the life cycles of hedge funds. The relationship is important as the understanding of the relationship helps investors to optimize future profits and for hedge fund managers to decide when it is appropriate to close the fund to new investments. Agarwal, Daniel and Naik (2003) and Goetzmann, Ingersoll and Ross (2003) find positive and concave relationship between returns and assets. However, they do not analyze the relationship for different hedge fund categories. Categories that hold illiquid assets, have limited market opportunities and high market impact of trades, are more likely to exhibit the concave relationship. Moreover, by optimizing returns, an optimal asset size can be calculated for funds in these categories.

7.1 Hypotheses

Hypothesis 5: The relationship between current performance and past assets is concave. By maximizing returns, an optimal asset size can be obtained for more illiquid categories.

7.2 Methodology

It is important that the dataset we are using does not have survivorship biases. According to Ackermann et al. (1999), termination and self-selection biases are the most powerful data-conditioning biases. Funds that are liquidated leave the database due to termination. Funds that choose not to be included in the database due to mergers, being closed to investors or a decision to discontinue advertising through the database due to sufficient funds, can voluntarily withdraw from the database. This induces a self-selection bias. Performance studies of existing hedge funds may be artificially inflated if poorly performing funds are systematically omitted from the database. Most databases with hedge fund data may contain various forms of conditioning bias. For mutual funds, Elton, Gruber, and Blake (1996), and Malkiel (1995) estimate that the inclusion of discontinued funds reduces the average annual mutual fund return by between 0.2 and 1.4 percentage points. Brown et al. (1999) find that the survivorship bias is about 3 percentage points per year for offshore hedge funds.

Hedge funds that leave due to self-selection are usually those that have raised enough capital and performed well enough that they do not see the need to be listed in the TASS database. One of the major reasons why hedge funds are voluntarily listed in the database is to obtain free advertising. Under Regulation D, that consists of rules governing the limited offer and sale of securities without registration under the Securities Act of 1933, specifically, Reg. 230.502. (c), hedge funds are banned from direct advertising. Hedge funds acquire new investors by using consultants, "word of mouth," or being listed in the database. Therefore, the self-selected hedge funds that left the database are eliminated from the analysis as the data on their returns and assets is not available after they choose to withdraw from the database.

There are two implications of the omission of the self-selected funds. First, if the asset size continues to grow in the future with increased returns, the true relationship might not exhibit the optimal fund size. However, the inclusion of the self-selected funds will negatively bias the optimal fund size. The second implication of the omission of the self-selected funds is that region A of the concave relationship between asset size and performance is omitted. In this case, the self-selection bias undermines the results of a concave relationship between a hedge fund asset size and returns (see Figure 1).

[INSERT FIGURE 1]

If hedge funds are subject to termination bias, then including such funds in the analysis would eliminate regions B and C (see Figure 2).

[INSERT FIGURE 2]

Hedge funds that are liquidated are more likely to be located in the regions B and C, and not adjusting for the termination bias would lead to an incorrect relationship between returns and performance.

In order to eliminate the self-selection bias, we examine all hedge funds in the "Graveyard" database, and eliminate funds that no longer report their performance, are closed to investment, or merged with other hedge funds. Therefore, in this Section we analyze 3,501 combined hedge funds, out of which 2,237 are in the "Successful" sub-database and 1,264 in the "Liquidated" sub-database. In order to eliminate the termination bias, performance and asset size values for hedge funds before 1994 are not considered. TASS started the "Graveyard" database in 1994. Therefore, the "Combined" database that consists of the "Successful" and "Liquidated" sub-databases does not have termination bias starting in 1994.

The relationship between returns and assets is further analyzed using monthly data.

$$r_{i,t} = \alpha_{i,t} + \beta_1 Assets_{i,t-1} + \beta_2 Assets^2_{i,t-1} + \epsilon_{i,t} \tag{17}$$

The returns versus assets are drawn in the Figure 3. The Figure is constructed as follows. First, assets are separated into 20 different bins according to asset sizes with an equal number of hedge funds. Then, for each bin, an average size and an average corresponding return is calculated. The relationship between the average returns and the average asset sizes is depicted in Figure 3.

[INSERT FIGURE 3]

7.3 Results

The results for regression 17 are specified in Table A.21.

[INSERT TABLE A.21]

The relationship between performance and asset size is positive (the coefficient= 0.290, t-stat=2.69); however, when the size squared is taken into account, the relationship is negative (the coefficient=-0.011, t-stat=-3.39). Therefore, the relationship between current returns and past assets is concave, suggesting that it is possible to obtain an optimal size for different hedge fund strategies. Note, when time effects are taken into the account, the relationship is still concave; however, the coefficient on the size squared is not significant at 5% level. This is due to category differences in the functional forms between returns and past assets as well as average assets and returns.

The relationship between returns and assets for all hedge funds is depicted in Figure 3. Volatility of returns versus assets is depicted in the Figure 4.

[INSERT FIGURE 3]

[INSERT FIGURE 4]

The relationship is concave, reaching an optimal size by optimizing returns. The asset size is optimal for a hedge fund investor, as the further increase in the asset size can actually decrease the return. The volatility decays with size according to a power law. Hedge funds that have a smaller asset size, usually younger hedge funds, tend to increase their riskiness in order to obtain high returns. As hedge funds become more mature and bigger in size, hedge fund managers employ less risky strategies. Also, the decrease in volatility can be explained by the diversification hypothesis: As funds become bigger, they have more flexibility of investing in more securities that are not correlated, thus reducing the variance of the overall portfolio.

We expect that the performance-asset relationship is different for various hedge fund strategies. Funds that invest in illiquid securities are more likely to exhibit a concave behavior than hedge funds that invest in liquid strategies. Funds in illiquid categories are also more likely to reach an optimal size in the analysis. These funds have larger market impact costs. Also, hedge funds that employ strategies with limited opportunities, such as

"Convertible arbitrage," "Event driven" and "Emerging market," are more likely to exhibit concave behavior in returns versus assets.

As can be seen in Figures 5 - 14, the performance-asset relationship is concave and reaches the optimal asset size for illiquid categories and categories with limited opportunities, such as "Convertible arbitrage" and "Emerging markets."

"Dedicated short bias", "Equity market neutral" and "Global macro" strategies that involve liquid instruments and have relatively unlimited opportunities, do not exhibit concave relationship between returns and assets under management. Interestingly, according to our analysis, it is possible to calculate an optimal size for a "Managed futures" strategy; however, the result is mainly driven by the outlier.

"Funds of funds" do exhibit a concave relationship between returns and assets; however, the fit is much better for "Convertible Arbitrage," "Emerging Markets," and all hedge funds taken together. "Funds of funds" are less likely to be affected by the diseconomies of scale than individual funds. Agarwal, Daniel, and Naik (2003) came to the same conclusion.

[INSERT FIGURES 5 - 14]

7.4 Performance Model

In order to be assured that the results for the concave relationship between returns and assets and the notion of optimal assets are not mechanical, Monte Carlo simulations of returns are performed. In the beginning of the simulation, we use 3,000 funds. The starting value for each hedge fund is $25 Million, and the cut-off liquidation value is $20 Million. Returns are normally distributed with the monthly μ=0.90% and the $\sigma = 6.58\%$. The simulation is run for 10 years.

Figure 15 shows the relationship between returns and assets using simulated data.

[INSERT FIGURE 15]

The relationship is random around the mean of 0.9%. There is no concave relationship between hedge funds returns and past assets. The proposed model takes into account only the distribution of returns and eliminates hedge funds after they reach a threshold of $20 million in assets. However, the data for the eliminated funds, as in TASS, is used in the analysis.

To make the model more realistic, we use parameters from previous sections of the paper. We adjust the performance for FAV, flows, competition and market impact.

Each month, returns are drawn from the Normal Distribution with $\mu = 0.90$ and $\sigma = 6.58$, $R^0_{i,t} = N(\mu, \sigma)$.

Flows are calculated as follows:

$$F_{i,t} = \begin{cases} 1 - exp(-r_{i,t-1}) & \text{if } r_{i,t-1} \geq 0 \\ -1 + exp(r_{i,t-1}) & \text{if } r_{i,t-1} < 0 \end{cases} \tag{18}$$

Using calculated F_t, DollarFlow, $DollF_t$ is calculated as follows:

$$F_{i,t} = \frac{DollF_{i,t}}{Assets_{i,t-1}} \tag{19}$$

Using calculated DollF and past assets, current assets are calculated using the following formula:

$$DollF_{i,t} = Assets_{i,t} - Assets_{i,t-1}(1 + R_{i,t}) \tag{20}$$

FAV, the favorable positioning metric is calculated as follows:

$$FAV_{k,t} = \frac{\sum_{i,i \in k} DollF_{i,t}}{\sum_{i,i \in POSNET} DollF_{i,t}} \tag{21}$$

POSNET is a subset of flows that are net positive during the time period t.

$$FAV_{k,t} = -\frac{\sum_{i,i\in k} DollF_{i,t}}{\sum_{i,i\in NEGNET} DollF_{i,t}} \tag{22}$$

NEGNET is a subset of flows that are net negative during the time period t. Competition, C, is measured as follows:

$$C_{k,t} = -\mu \exp^{FAV_{i,t-1}-1} \tag{23}$$

New Entry into category k is calculated as follows:

$$ENTRY_{k,t} = INTEGER(\sqrt{NUMBER_{t-1}}FAV_{t-1}) \tag{24}$$

where $NUMBER_{t-1}$ is the number of hedge funds in category k in the previous time period.

Market Impact, M, for each hedge fund i at time t is calculated as follows:

$$M_{i,t} = -0.2\frac{Assets_{i,t-1}}{\sum_{i,i\in k} Assets_{i,t-1}} \tag{25}$$

Return is given by:

$$R_{i,t} = R^0_{i,t} + C_{k,t} + M_{i,t} \tag{26}$$

Each fund starts with $40 Million. The cut-off for hedge fund liquidation is $20 Million. There are 10 categories, and each category starts off with 100 hedge funds. The model is run for 10 years. The results are depicted in Figure 16.

[INSERT FIGURE 16]

As can be seen from this figure, the relationship between returns and assets is concave and reaches an optimal asset size. The relationship resembles the real data depicted in Figure 3.

The same model is run for 20 years, and the second 10 years of data are taken for the analysis. The results are presented in Figure 17.

[INSERT FIGURE 17]

The same model is run for 50 years, and the last 10 years of data are taken for the analysis. The results are presented in Figure 18.

[INSERT FIGURE 18]

Using these results, we can see the progression of the performance-asset size relationship over time. In the first 10 years, the number of funds is relatively small compared to the number of funds in 50 years. Therefore, the market impact, which is a function of a fraction of total assets in a category, greatly affects the performance of the funds. In 50 years, as more competitors come in, the fraction of asset size for each competitor decreases, reducing market impact. Therefore, in Figure 16 we see negative returns with high assets due to high market impact. That effect diminishes in Figure 18. The concave relationship in all figures is due to competition and market impact effects. As more new hedge funds enter, competitors have to compete for limited opportunities as well as limited capital, thus, reducing returns of the funds in that category.

8 Conclusions

The paper explores the drivers of life cycles of hedge funds. Compared to mutual funds, hedge funds have a very large probability of liquidation. The annual attrition in hedge funds due to liquidation averaged 7.10% between 1994-2002. The paper studies the impact of age, size, returns, flows, favorable positioning and competition on the life cycles of hedge funds. Performance and flows positively affect the survival probability. The relationship between performance and fund flows is studied. The piecewise linear relationship is estimated and applied to different hedge fund categories. The performance-flow relationship is positive and concave. As expected, hedge funds that follow more directional strategies are more likely to have a higher effect of past returns on future flows than funds with more event-driven strategies.

We propose that favorable positioning positively affects the survival probability of a hedge fund. Therefore, being in the right category at the right time can reduce the liquidation probability for a hedge fund, after adjusting for fund characteristics. On the other hand, competition among hedge funds in the same category greatly increases the liquidation probability of an individual hedge fund in that category. As a result, hedge fund managers might choose to stay in the category which experiences favorable positioning and less competition. However, it is shown that as the hedge fund category becomes more favorable, more hedge funds enter such a category, thus increasing the competition. As investors chase category returns, competition among hedge funds within the category increases, thus, liquidation probability of hedge funds in that category increases. Therefore, hedge fund managers should dynamically weigh the risks of being in a particular category at any time and understand the interrelationships between competition and favorable positioning. Smaller hedge funds are less likely to increase liquidation probability. We also find that as competition increases, marginal funds are more likely to be liquidated than funds that deliver superior risk-adjusted returns.

Past asset size also impacts current hedge fund returns that in turn affect the life cycle of hedge funds. The relationship between current performance and past asset size is positive and concave. It is possible to obtain an optimal asset size by optimizing returns. Therefore, hedge fund investors should be wary of hedge fund asset size before investing, and try to invest in a hedge fund that is near its optimal size. Hedge fund managers might be more inclined to increase the asset base, thereby increasing the fees. Therefore, it is in the best interest of an investor to choose hedge fund strategies that do not have asset size higher than the optimum. The performance-asset size relationship takes on different functional forms for different categories. The relationship is concave and the optimal size can be obtained for more illiquid categories such as "Emerging markets" and "Convertible arbitrage." These hedge fund categories experience high market impact and are subject to limited opportunities. 'Funds of funds" are less likely to be affected by the diseconomies of scale than individual funds. Hedge fund managers with high asset sizes might choose to close the fund to new investors before facing a decrease in returns and an increase in liquidation probabilities.

In order to understand the life cycles of hedge funds, it is important to understand the interrelationships of fund characteristics – flows, returns, asset size and age – and industry characteristics – favorable positioning and competition –. For hedge fund managers, the benefit of this approach will be an improved understanding of the effects of survival probabilities. For hedge fund investors, the benefit will be an improved understanding of investment opportunities. Next step would be to propose theoretical models for the optimal dynamic strategies for hedge fund managers and investors given the factors outlined in the paper. This is the focus of our future research.

A Appendix

A.1 Tables and Figures

Code	Category	Number of Funds In:		
		Combined	Successful	Liquidated
1	Convertible Arbitrage	143	117	26
2	Dedicated Short Bias	23	15	8
3	Emerging Markets	219	107	112
4	Equity Market Neutral	190	136	54
5	Event Driven	304	227	77
6	Fixed Income Arbitrage	138	88	50
7	Global Macro	181	84	97
8	Long/Short Equity	1139	779	360
9	Managed Futures	421	164	257
10	Fund of Funds	657	458	199
11	Other	86	62	24
	All	3501	2237	1264

Table A.1: This table presents the number of funds in the TASS Hedge Fund Combined, Successful and Liquidated databases during the period from January 1994 to December 2002.

Year	Existing Funds	New Entries	New Exits	Intrayear Entry/Exit	Total Funds	Attrition Rate (%)
1977	0	3	0	0	3	0.0
1978	3	2	0	0	5	0.0
1979	5	2	0	0	7	0.0
1980	7	3	0	0	10	0.0
1981	10	3	0	0	13	0.0
1982	13	4	0	0	17	0.0
1983	17	8	0	0	25	0.0
1984	25	14	0	0	39	0.0
1985	39	9	0	0	48	0.0
1986	48	21	0	0	69	0.0
1987	69	27	0	0	96	0.0
1988	96	31	0	0	127	0.0
1989	127	43	0	0	170	0.0
1990	170	102	0	0	272	0.0
1991	272	86	0	0	358	0.0
1992	358	155	0	0	513	0.0
1993	513	230	0	0	743	0.0
1994	743	255	19	1	998	2.6
1995	998	289	60	1	1287	6.0
1996	1287	310	119	9	1597	9.3
1997	1597	349	93	6	1946	5.8
1998	1946	325	162	9	2271	8.3
1999	2271	363	183	7	2634	8.1
2000	2634	330	231	9	2964	8.8
2001	2964	355	260	5	3319	8.8
2002	3319	246	275	12	3565	8.3

Table A.2: This table presents the annual number of entries into and exits out of the TASS Hedge Fund Database from January 1994 to December 2002.

Fund Characteristics	Hedge Funds		Funds of Funds	
	Mean	Median	Mean	Median
Monthly Return %	0.90	0.79	0.59	0.59
Standard Deviation of Monthly Returns %	6.58	–	3.68	–
Age (Months)	46.36	35.00	52.53	42.00
Assets (Million US Dollars)	81.77	20.00	67.59	18.39
Favorable Positioning (FAV)(per quarter)	0.07	0.09	0.03	0.13
Standard Deviation of Favorable Positioning (FAV)(per quarter)	0.30	–	0.23	–
NUMBER (per quarter)	307.11	228.00	332.75	369.00
Standard Deviation of NUMBER (per quarter)	223.32	–	64.96	–

Table A.3: This table shows median and average monthly returns, standard deviation of monthly returns, age, assets under management, favorable positioning (FAV) metric, standard deviation for the FAV, the number of competitors in a particular category (NUMBER), and the standard deviation for the number of competitors in a particular category for single-manager hedge funds and for funds of funds. The statistics are calculated using the TASS Database from January 1994 to December 2002.

Parameter	Estimate	t-Statistic
$\alpha_{i,t}$	0.679^*	8.05
$Return_{i,t}$	0.234^*	5.82
$Trank^1_{i,t-1} - BottomTercile$	0.293^*	5.46
$Trank^2_{i,t-1} - MiddleTercile$	0.269^*	5.51
$Trank^3_{i,t-1} - TopTercile$	0.006	0.08
$Flow_{i,t-1}$	0.048^*	4.56
$Size_{i,t-1}$	-0.041^*	-8.32
$Age_{i,t-1}$	-0.001^*	-9.71
$\sigma_{i,t-1}$	-0.002	-1.19

Table A.4: This table reports the Fama-MacBeth results of regression of current flows $Flow_{i,t}$ on Bottom, Middle and Top Terciles of past quarter performance, past flows $Flow_{i,t-1}$, last quarter's asset size $Size_{i,t-1}$, past age $Age_{i,t-1}$, last quarter's standard deviation of monthly returns $\sigma_{i,t-1}$ and categories of hedge funds. Funds of funds are omitted from the model. The R^2 for the regression is 5.53%. Quarterly data from 1994 to 2002 is used. The regression is adjusted for category effects. Figures with * are significant at 5% level.

Category	$\alpha_{i,t}$		$Return_{i,t}$		$Trank^1_{i,t-1}$		$Trank^2_{i,t-1}$		$Trank^3_{i,t-1}$		$Flow_{i,t-1}$		$Size_{i,t-1}$		$Age_{i,t-1}$		$\sigma_{i,t-1}$	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Convertible Arbitrage	0.695	0.341	1.417	0.593	0.350	0.140	0.208	0.169	0.185	0.202	0.056	0.042	−0.042	0.020	−0.002	0.001	0.002	0.015
Dedicated Short Bias	-0.304	0.333	0.383	0.657	0.783	0.628	0.472	0.229	0.189	0.157	0.605	0.183	0.004	0.016	−0.001	0.001	−0.031	0.018
Emerging Markets	0.242	0.172	0.227	0.114	0.406	0.099	−0.013	0.071	0.082	0.087	0.095	0.050	−0.018	0.010	−0.001	0.000	−0.002	0.003
Equity Market Neutral	1.333	0.382	0.024	0.593	0.431	0.222	0.189	0.210	0.609	0.364	0.086	0.057	−0.077	0.021	−0.002	0.001	−0.017	0.012
Event Driven	0.876	0.382	0.165	0.244	0.458	0.138	−0.038	0.078	0.230	0.128	0.076	0.032	−0.051	0.023	−0.001	0.000	−0.011	0.003
Fixed Income Arbitrage	1.041	0.565	0.121	0.256	0.470	0.284	0.357	0.247	0.347	0.370	−0.165	0.260	−0.065	0.032	−0.001	0.000	−0.008	0.011
Global Macro	0.360	0.173	0.132	0.146	0.134	0.114	0.243	0.166	0.174	0.166	0.176	0.063	−0.021	0.009	−0.001	0.000	−0.007	0.005
Long/Short Equity	0.575	0.1112	0.225	0.052	0.297	0.062	0.256	0.086	−0.001	0.092	0.120	0.019	−0.036	0.006	−0.001	0.000	−0.004	0.001
Managed Futures	0.411	0.147	0.186	0.089	0.371	0.242	0.259	0.130	−0.116	0.208	0.136	0.033	−0.034	0.013	−0.001	0.000	0.008	0.006
Fund of Funds	0.262	0.082	0.190	0.094	0.282	0.075	0.049	0.046	0.176	0.053	0.198	0.035	−0.018	0.005	−0.001	0.000	−0.008	0.002
Other	1.308	0.602	0.937	0.747	0.346	0.690	0.031	0.219	0.262	0.242	0.210	0.131	−0.079	0.035	−0.002	0.002	−0.017	0.018

Table A.5: This table reports the Fama-MacBeth results of regression of current flows $Flow_{i,t}$ on Bottom, Middle and Top Terciles of past quarterly performance, past flows $Flow_{i,t-1}$, last quarter's asset size $Size_{i,t-1}$, past age $Age_{i,t-1}$, and last quarter's standard deviation of monthly returns $\sigma_{i,t-1}$ for 11 hedge fund categories.

Code	Category	Estimate
1	Convertible Arbitrage	0.21
2	Dedicated Short Bias	0.47
3	Emerging Markets	-0.01
4	Equity Market Neutral	0.19
5	Event Driven	-0.04
6	Fixed Income Arbitrage	0.36
7	Global Macro	0.24
8	Long/Short Equity	0.26
9	Managed Futures	0.26
10	Fund of Funds	0.05
11	Other	0.03
	All	0.27

Table A.6: This table presents the estimates of the Middle Tercile of past quarterly returns for 11 categories.

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square
$\alpha_{i,t}$	-1.823^{*}	0.586	9.670	0.002
$Age_{i,t}$	0.001	0.001	0.028	0.867
$r_{i,t-1}$	-2.677^{*}	0.356	56.659	< 0.001
$r_{i,t}$	-3.362^{*}	0.330	103.774	< 0.001
$Flow_{i,t-1}$	-0.790^{*}	0.192	16.991	< 0.001
$Assets_{i,t-1}$	-0.399^{*}	0.027	224.442	< 0.001

Table A.7: This table reports the results of logit regression of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarterly return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$), previous quarterly flow into the fund ($Flow_{i,t-1}$) and previous assets under management $Assets_{i,t-1}$. The R^2 is 13.62%. The model adjusts for time and category effects. Figures with * are significant to 5% level.

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square
$\alpha_{i,t}$	-5.103^*	0.411	154.568	< 0.001
$Age_{i,t}$	0.010	0.059	0.028	0.867
$r_{i,t-1}$	-0.076^*	0.010	56.659	< 0.001
$r_{i,t}$	-0.090^*	0.009	103.774	< 0.001
$Flow_{i,t-1}$	-0.105^*	0.025	16.991	< 0.001
$Assets_{i,t-1}$	-6.666^*	0.027	224.442	< 0.001

Table A.8: This table reports the results of logit regression of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarterly return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$), previous quarterly flow into the fund ($Flow_{i,t-1}$) and previous assets under management $Assets_{i,t-1}$. All variables are adjusted for the mean. The R^2 is 13.62%. The model adjusts for time and category effects. Figures with * are significant to 5% level.

Test	Chi-Square	Degrees of Freedom	Pr > Chi-Square
Likelihood Ratio	739.795	53	< 0.001
Score	801.630	53	< 0.001
Wald	687.167	53	< 0.001

Table A.9: This table reports the results of a test for global null hypothesis that BETA=0 for logit regression of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarterly return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$), previous quarterly flow into the fund ($Flow_{i,t-1}$) and previous assets under management $Assets_{i,t-1}$. The model adjusts for time and category effects.

Parameter	Estimate	t-Statistic
$\alpha_{k,t}$	-0.041	-1.16
$r_{k,t-1}$	1.357	1.85

Table A.10: This table reports Fama-MacBeth regression of favorable positioning (FAV) on past quarter category return $r_{k,t-1}$. The category return is value-weighted. The R^2 for this regression is 28.46%.

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square
$\alpha_{i,t}$	1.631*	0.590	7.649	0.006
$Age_{i,t}$	0.002	0.001	2.170	0.141
$r_{i,t-1}$	−2.685*	0.357	56.459	< 0.001
$r_{i,t}$	−3.440*	0.331	108.031	< 0.001
$FAV_{k,t-1}$	−0.502*	0.183	7.501	0.006
$Assets_{i,t-1}$	−0.405*	0.026	238.018	< 0.001

Table A.11: This table reports the results of logit regression of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarterly return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$), previous favorable positioning of the hedge fund category compared to other categories in the database ($FAV_{k,t-1}$) and previous assets under management $Assets_{i,t-1}$. The R^2 for the regression is 13.24%. The model adjusts for time and category effects. Figures with * are significant to 5% level.

Test	Chi-Square	Degrees of Freedom	Pr > Chi-Square
Likelihood Ratio	727.056	53	< 0.001
Score	811.074	53	< 0.001
Wald	682.541	53	< 0.001

Table A.12: This table reports the results of a test for global null hypothesis that BETA=0 for logit regression of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarter return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$), previous favorable positioning of the hedge fund category compared to other categories in the database ($FAV_{k,t-1}$) and previous assets under management $Assets_{i,t-1}$. The model adjusts for time and category effects.

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square
$\alpha_{i,t}$	1.737*	0.588	8.734	0.003
$Age_{i,t}$	0.002	0.001	2.560	0.110
$r_{i,t-1}$	−2.593*	0.360	51.999	< 0.001
$r_{i,t}$	−3.396*	0.332	104.420	< 0.001
$Number_{k,t-4}$	0.002*	0.001	6.945	0.008
$Assets_{i,t-1}$	−0.412*	0.027	241.442	< 0.001

Table A.13: This table reports the results of logit regression of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarterly return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$), the number of hedge funds in a particular category a year before ($Number_{k,t-4}$) and previous assets under management $Assets_{i,t-1}$. The R^2 is 12.30%. The model adjusts for time and category effects. Figures with * are significant to 5% level.

Test	Chi-Square	Degrees of Freedom	Pr > Chi-Square
Likelihood Ratio	653.078	46	< 0.001
Score	754.083	46	< 0.001
Wald	666.474	46	< 0.001

Table A.14: This table reports the results of a test for global null hypothesis that BETA=0 for logit regression of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarterly return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$), the number of hedge funds in a particular category a year before ($Number_{k,t-4}$) and previous assets under management $Assets_{i,t-1}$. The model adjusts for time and category effects.

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square
$\alpha_{i,t}$	1.579*	0.596	7.028	0.008
$Age_{i,t}$	0.002	0.001	2.555	0.110
$r_{i,t-1}$	−2.593*	0.360	51.932	< 0.001
$r_{i,t}$	−3.400*	0.332	104.750	< 0.001
$Number_{k,t-4}$	0.001*	0.000	4.267	0.039
$FAV_{k,t-1}$	−0.416*	0.192	4.674	0.031
$Assets_{i,t-1}$	−0.411*	0.027	240.513	< 0.001

Table A.15: This table reports the results of logit regression of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarterly return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$), the number of hedge funds in a particular category a year before ($Number_{k,t-4}$), previous favorable positioning of the hedge fund category compared to other categories in the database ($FAV_{k,t-1}$) and previous assets under management $Assets_{i,t-1}$. The R^2 is 12.38%. The model adjusts for time and category effects. Figures with * are significant to 5% level.

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square
$\alpha_{i,t}$	-4.979^{*}	0.447	124.118	< 0.001
$Age_{i,t}$	0.090	0.057	2.555	0.110
$r_{i,t-1}$	-0.074^{*}	0.010	51.932	< 0.001
$r_{i,t}$	-0.091^{*}	0.009	104.750	< 0.001
$Number_{k,t-4}$	0.416^{*}	0.202	4.267	0.039
$FAV_{k,t-1}$	-0.027^{*}	0.013	4.674	0.031
$Assets_{i,t-1}$	-6.872^{*}	0.443	240.513	< 0.001

Table A.16: This table reports the results of logit regression of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarterly return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$), the number of hedge funds in a particular category a year before ($Number_{k,t-4}$), previous favorable positioning of the hedge fund category compared to other categories in the database ($FAV_{k,t-1}$) and previous assets under management $Assets_{i,t-1}$. All variables are adjusted for the mean. The R^2 is 12.38%. The model adjusts for time and category effects. Figures with * are significant to 5% level.

Test	Chi-Square	Degrees of Freedom	Pr > Chi-Square
Likelihood Ratio	657.	74647	< 0.001
Score	756.373	47	< 0.001
Wald	671.032	47	< 0.001

Table A.17: This table reports the results of a test for global null hypothesis that BETA=0 for logit regression of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarterly return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$), the number of hedge funds in a particular category a year before ($Number_{k,t-4}$), previous favorable positioning of the hedge fund category compared to other categories in the database ($FAV_{k,t-1}$) and previous assets under management $Assets_{i,t-1}$. The model adjusts for time and category effects.

Variable	$TOTLIQ_{i,t}$	$Age_{i,t}$	$r_{i,t-1}$	$r_{i,t}$	$Flow_{i,t-1}$	$Flow_{i,t}$	$FAV_{k,t-1}$	$Assets_{i,t-1}$	$Number_{k,t-4}$
$TOTLIQ_{i,t}$	1.000	0.022	−0.082	−0.056	−0.075	−0.049	−0.022	−0.102	0.001
$Age_{i,t}$	0.022	1.000	−0.083	−0.077	−0.249	−0.243	−0.043	0.281	0.026
$r_{i,t-1}$	−0.082	−0.083	1.000	0.078	0.084	0.211	0.010	0.024	−0.047
$r_{i,t}$	−0.056	−0.077	0.098	1.000	0.023	0.083	−0.0145	−0.028	−0.060
$Flow_{i,t-1}$	−0.075	−0.249	0.084	0.023	1.000	0.355	0.151	0.092	0.019
$Flow_{i,t}$	−0.049	−0.243	0.211	0.083	0.355	1.000	0.100	−0.024	0.011
$FAV_{k,t-1}$	−0.022	−0.043	0.010	−0.015	0.151	0.100	1.000	0.104	0.359
$Assets_{i,t-1}$	−0.102	0.281	0.024	−0.028	0.092	−0.024	0.104	1.000	0.012
$Number_{k,t-4}$	0.001	0.026	−0.047	−0.060	0.019	0.011	0.359	0.012	1.000

Table A.18: This table reports the results for quarterly Spearman correlation of $TOTLIQ_{i,t}$, $Age_{i,t}$, $r_{i,t-1}$, $r_{i,t}$, $Flow_{i,t-1}$, $Flow_{i,t}$, $FAV_{k,t-1}$, $Assets_{i,t-1}$ and $Number_{k,t-4}$.

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square
$\alpha_{i,t}$	2.017*	0.592	11.607	< 0.001
$Age_{i,t}$	0.002	0.001	1.832	0.176
$r_{i,t-1}$	−2.413*	0.362	44.446	< 0.001
$r_{i,t}$	−3.344*	0.339	97.335	< 0.001
$Number_{k,t-1}$	0.019*	0.002	132.944	< 0.001
$Frac_{k,t-1}$	−0.660*	0.047	201.447	< 0.001
$Assets_{i,t-1}$	−0.388*	0.027	209.622	< 0.001

Table A.19: This table reports the results of logit regression of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarterly return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$),the number of hedge funds in a particular category a quarter before ($Number_{k,t-1}$), the fraction of the number of hedge funds in a category divided by the total assets under management in that category ($Frac_{k,t-1}$) and previous assets under management $Assets_{i,t-1}$. The R^2 is 18.65%. The model adjusts for time and category effects. Figures with * are significant to 5% level.

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > Chi-Square
$r_{i,t-1}$ - Comp 1	−0.029	0.026	1.203	0.273
$r_{i,t-1}$ - Comp 2	−0.063*	0.022	8.021	0.005
$r_{i,t-1}$ - Comp 3	−0.066*	0.020	11.416	0.001
$r_{i,t-1}$ - Comp 4	−0.089*	0.026	11.910	0.001
$r_{i,t-1}$ - Comp 5	−0.115*	0.021	31.308	< 0.001
$r_{i,t-1}$ - Comp 1-5	−0.074*	0.010	51.932	< 0.001

Table A.20: This table reports the results of logit regressions of probability of liquidation of a hedge fund at time t on intercept, current age ($Age_{i,t}$), previous quarterly return on investments ($r_{i,t-1}$), current quarterly return ($r_{i,t}$), the number of hedge funds in a particular category a year before ($Number_{k,t-4}$), favorable positioning (FAV) and previous assets under management $Assets_{i,t-1}$ for 5 different terciles of competition, where Comp 1 represents the lowest tercile, and Comp 5 represents the highest tercile. All variables are adjusted for the mean. The coefficients on the past return are shown. The models adjust for time and category effects. Figures with * are significant to 5% level.

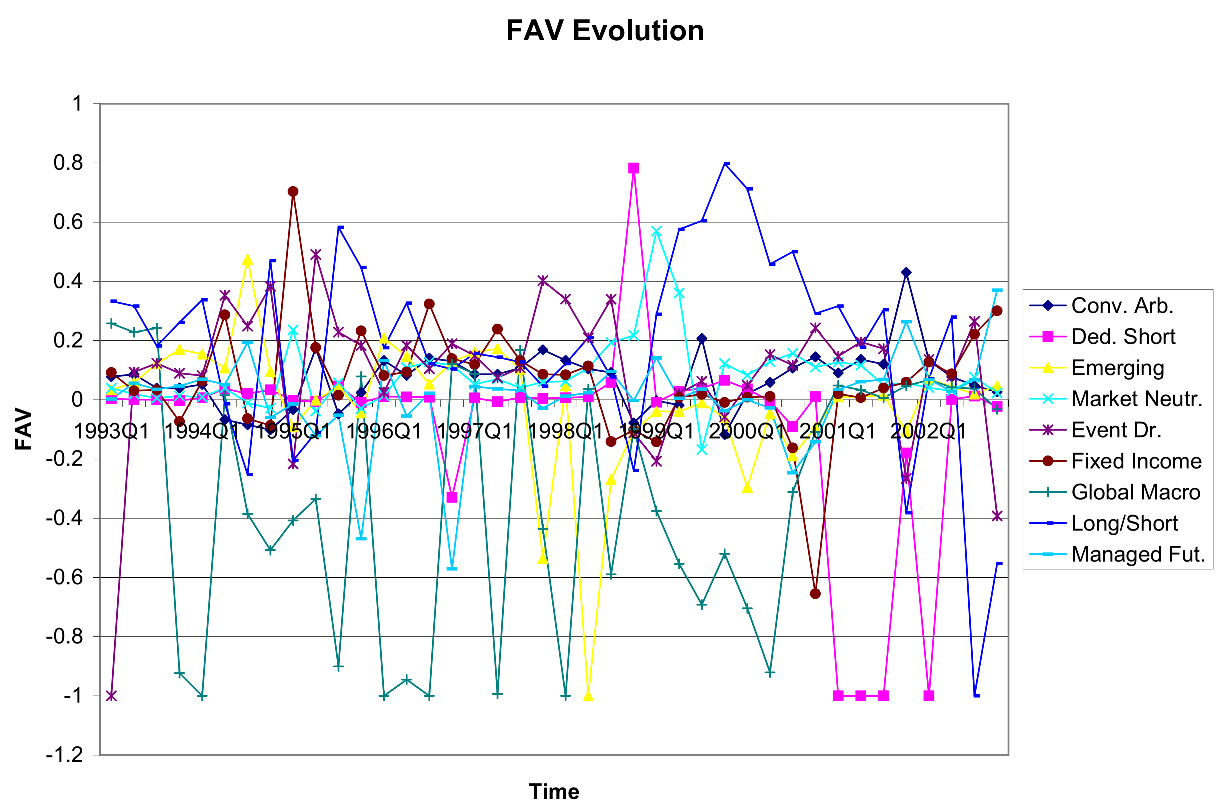

Figure A.1. This figure depicts FAV metric over time for 11 categories.

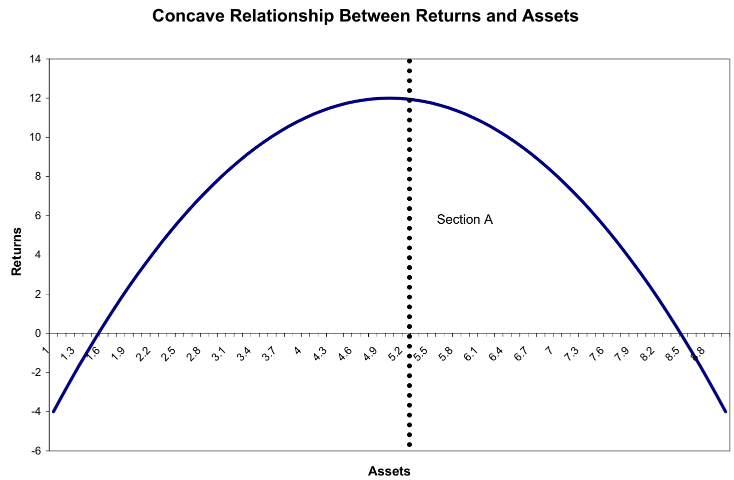

Figure 1: This figure shows that if the data are not adjusted for the self-selection bias, then the section A is going to be eliminated from the analysis.

Parameter	Estimate	t-Statistic
$\alpha_{i,t}$	-0.911	-1.02
$Assets_{i,t-1}$	0.290^{*}	2.69
$Assets^2_{i,t-1}$	-0.011^{*}	-3.39

Table A.21: This table reports the results of linear regression of a monthly return of a hedge fund on $Assets_{i,t-1}$ and $Assets^2_{i,t-1}$. Note, assets are measured in natural logarithm quantities. The R^2 for this regression is 0.05%. Figures with * are significant at 5% level.

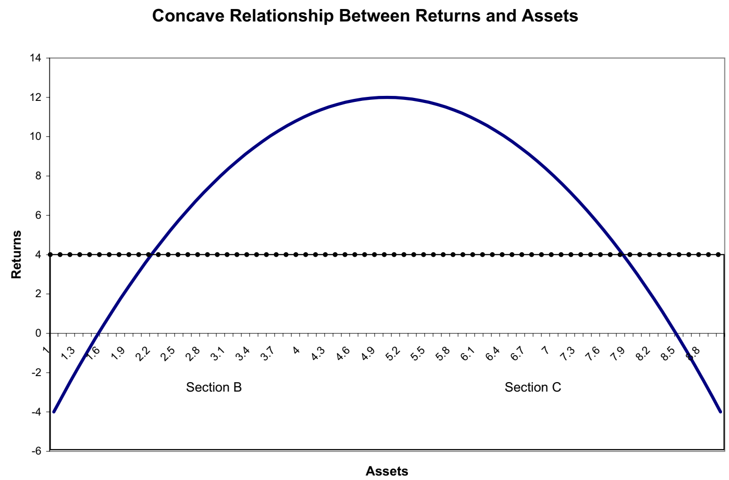

Figure 2: This figure shows that if the data are not adjusted for the termination bias, then the sections B and C are going to be eliminated from the analysis.

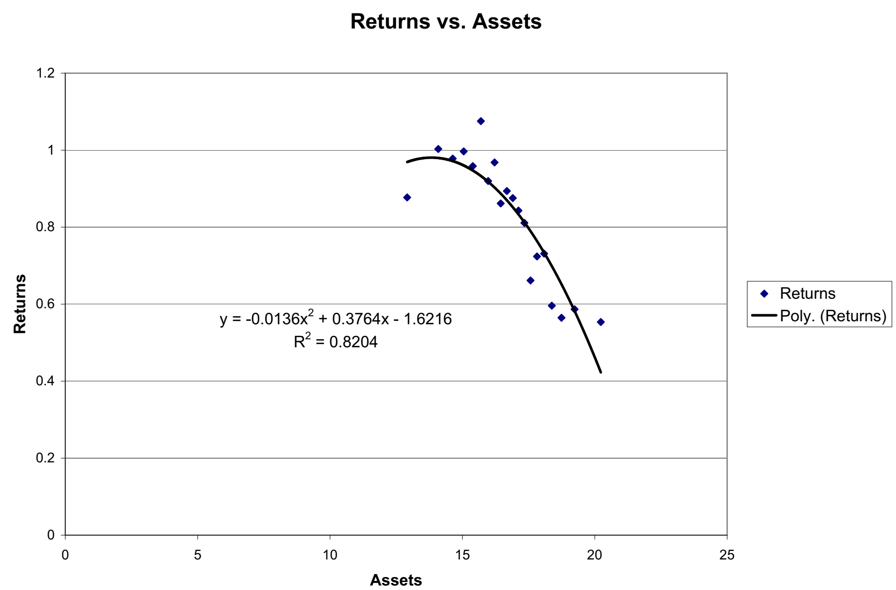

Figure 3: This figure shows the relationship between returns and assets for all hedge funds. The data are adjusted for termination and self-selection biases.

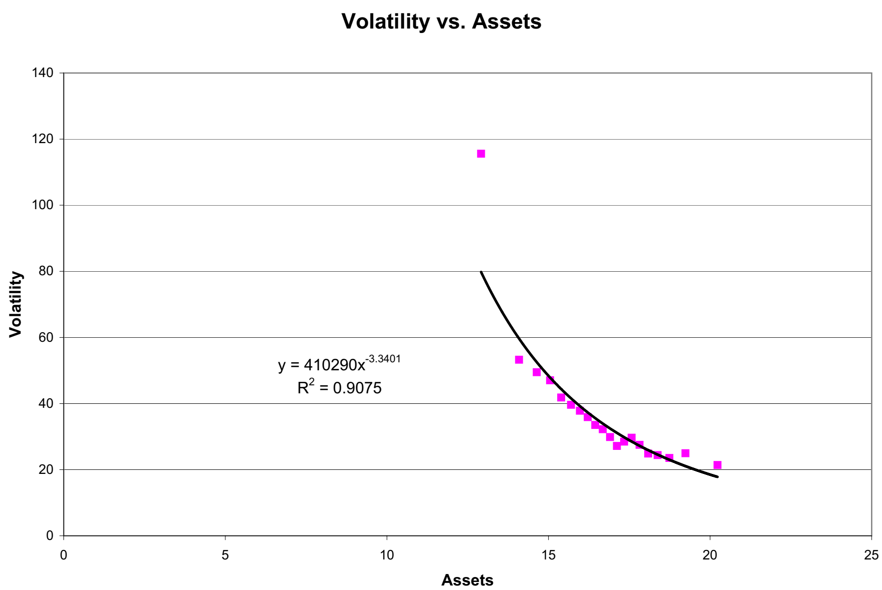

Figure 4: This figure shows the relationship between volatility of returns and assets for all hedge funds. The data are adjusted for termination and self-selection biases.

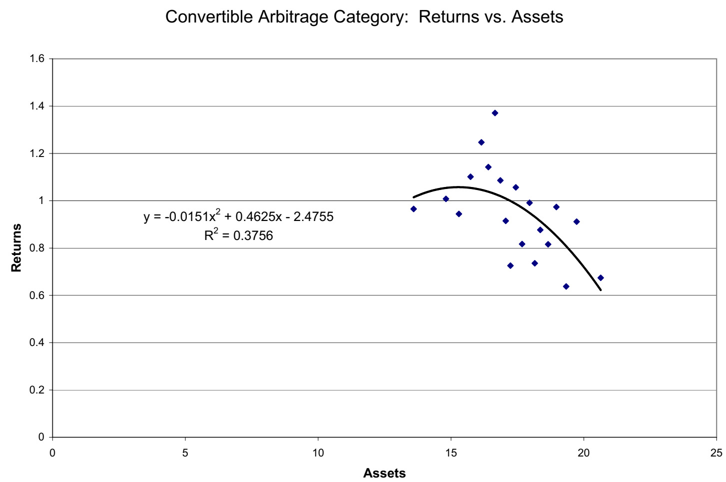

Figure 5: Returns vs. Assets relationship for the Convertible Arbitrage Category.

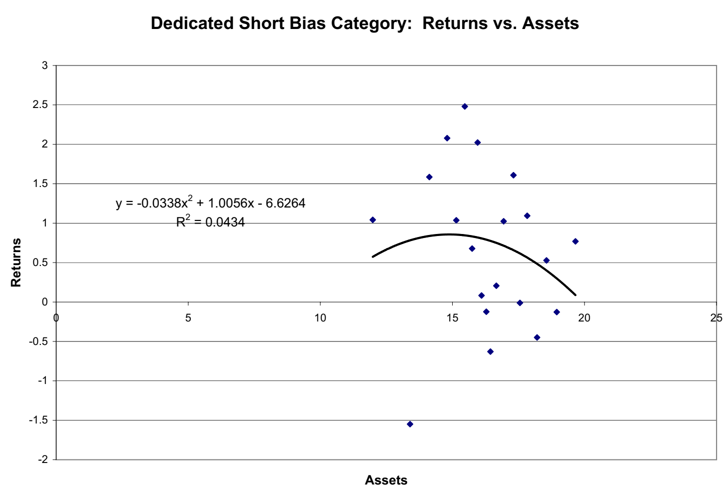

Figure 6: Returns vs. Assets relationship for the Dedicated Short Bias Category.

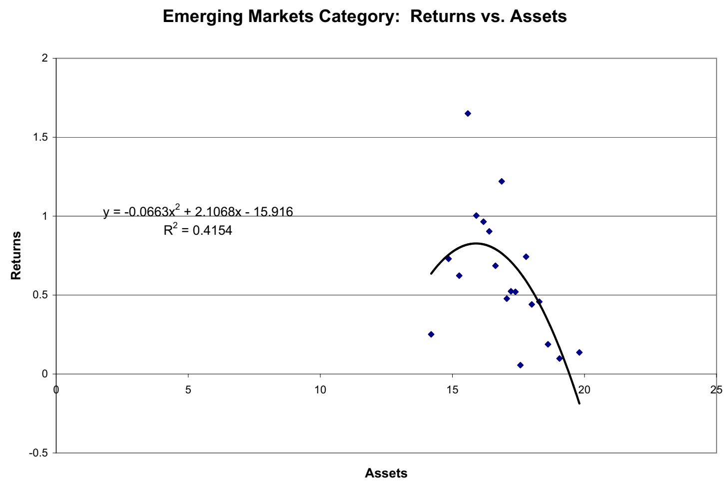

Figure 7: Returns vs. Assets relationship for the Emerging Markets Category. Note, the outlier (Assets=13.16, Returns=2.02%) is taken out of the picture.

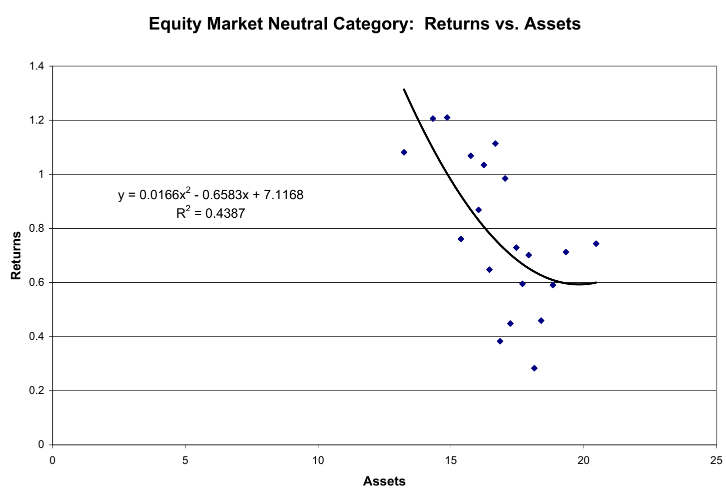

Figure 8: Returns vs. Assets relationship for the Equity Market Neutral Category.

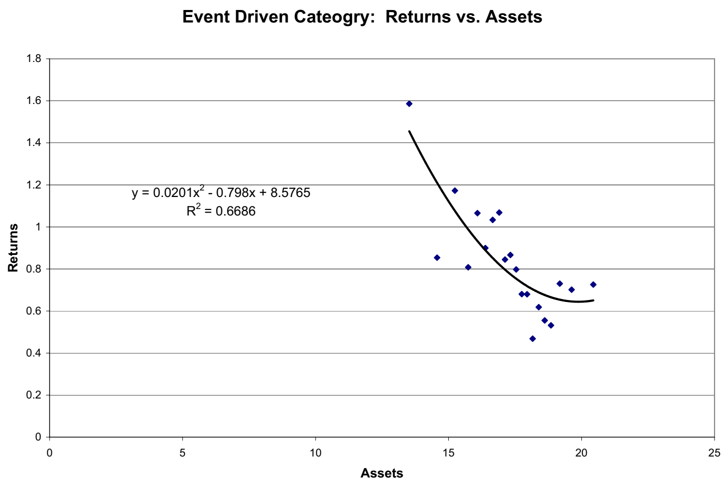

Figure 9: Returns vs. Assets relationship for the Event Driven Category.

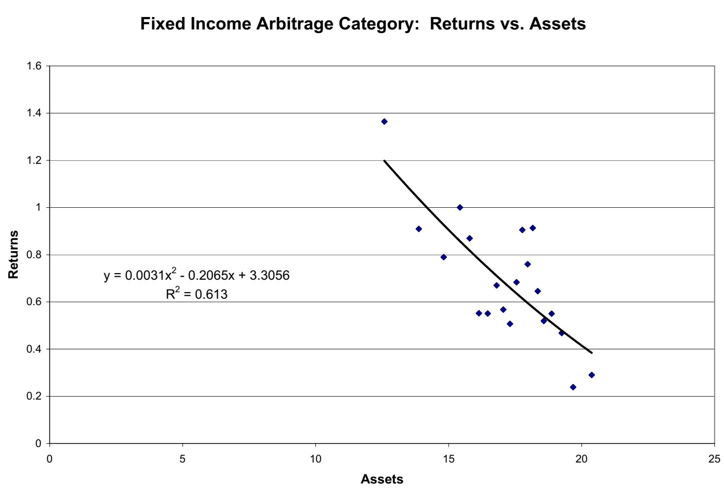

Figure 10: Returns vs. Assets relationship for the Fixed Income Arbitrage Category.

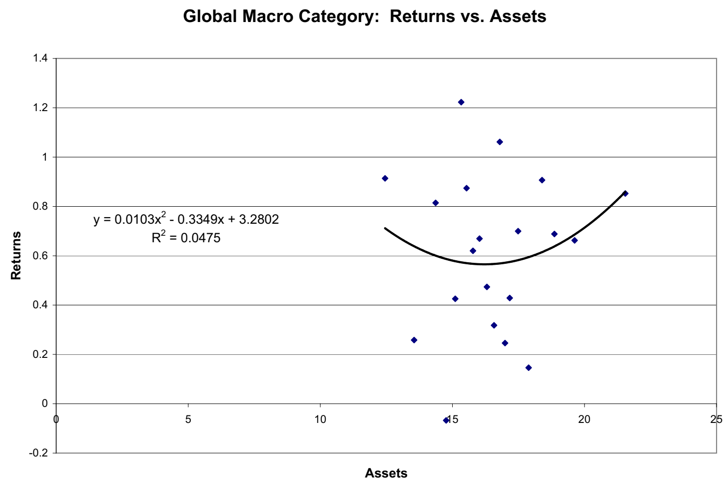

Figure 11: Returns vs. Assets relationship for the Global Macro Category.

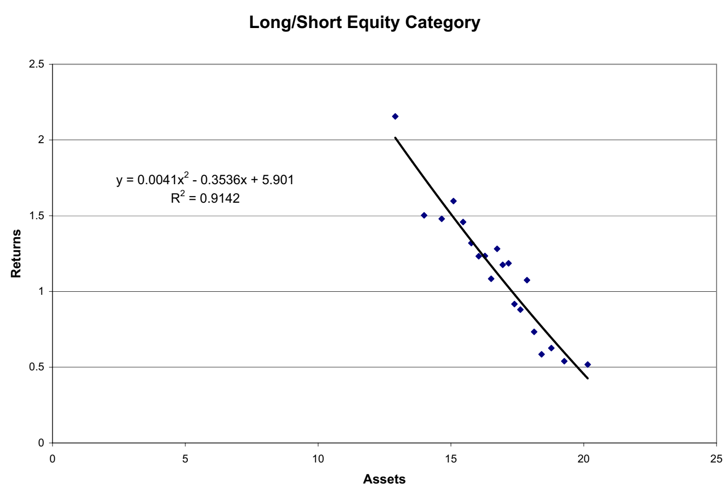

Figure 12: Returns vs. Assets relationship for the Long/Short Equity Category.

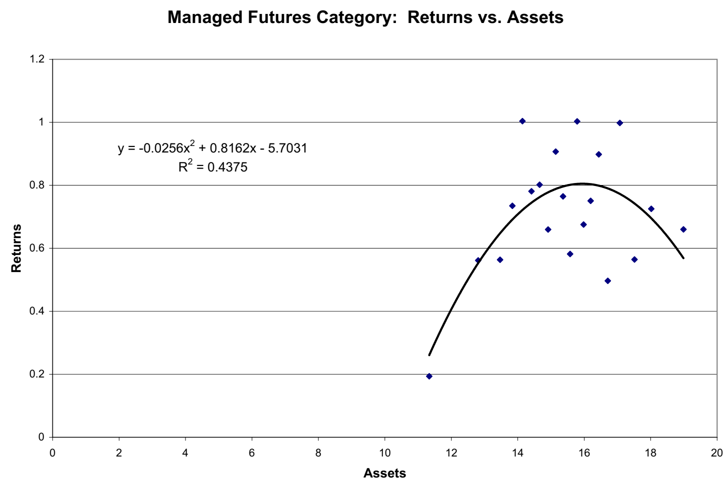

Figure 13: Returns vs. Assets relationship for the Managed Futures Category.

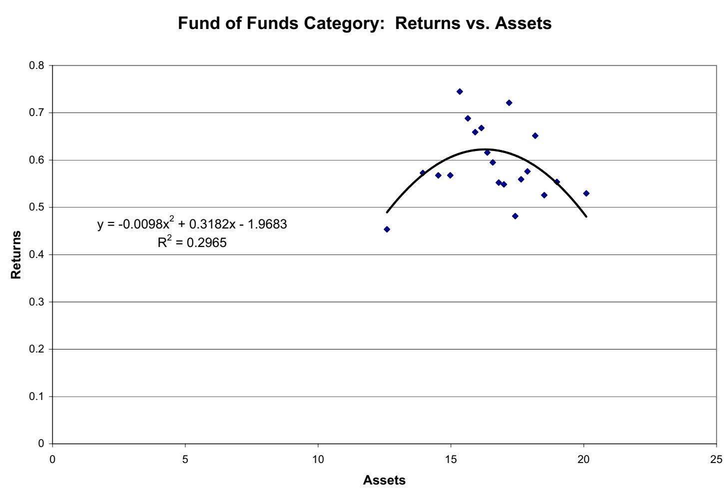

Figure 14: Returns vs. Assets relationship for the Fund of Funds Category.

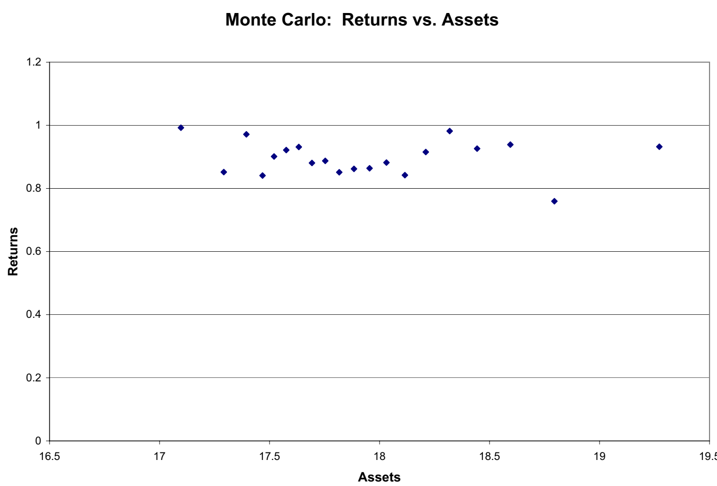

Figure 15: This figure shows the relationship between returns and assets using simulated data. In the beginning of the simulation, 3,000 funds enter. The starting value is \$40 Million, and the cut-off liquidation value is \$20 Million. Returns are normally distributed with the monthly μ=0.90% and the $\sigma = 6.58\%$. The Monte Carlo simulation is run for 10 years (120 months).

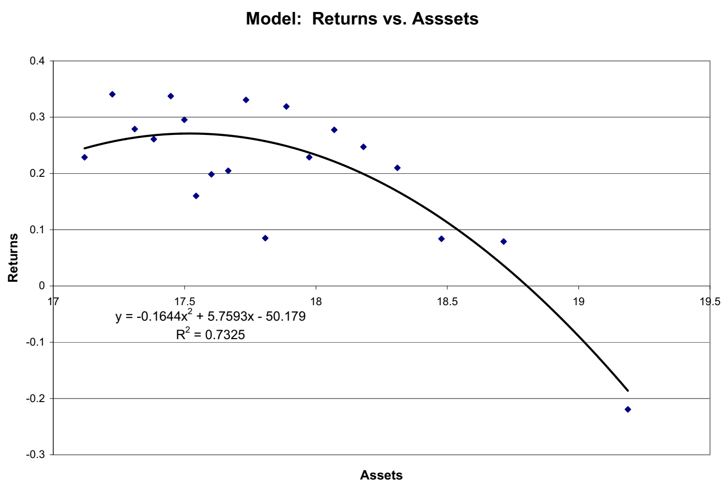

Figure 16: This figure shows the relationship between returns and assets using simulated data. Each month, returns are drawn from the Normal Distribution with the monthly μ=0.90% and the σ = 6.58%. In the beginning of the simulation, 100 funds enter into each of 10 categories. The starting value is $40 Million, and the cut-off liquidation value is $20 Million. New funds are allowed to enter during the simulation. Returns are adjusted for competition between categories, favorable positioning and market impact. The simulation is run for 10 years.

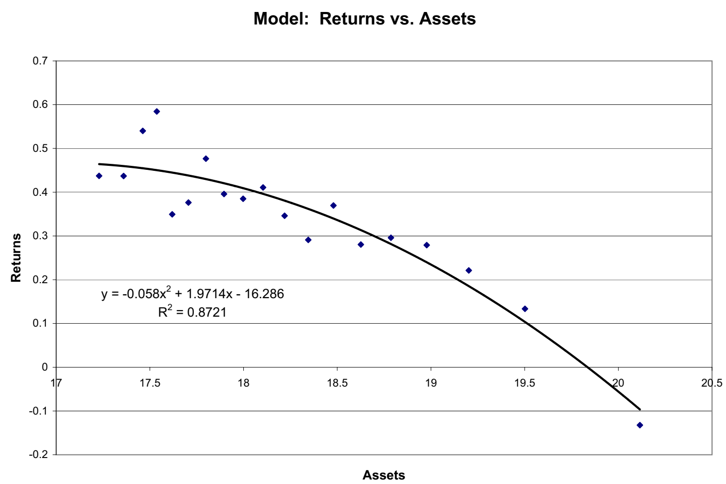

Figure 17: This figure shows the relationship between returns and assets using simulated data. Each month, returns are drawn from the Normal Distribution with μ=0.90% and the σ = 6.58%. In the beginning of the simulation, 100 funds enter into each of 10 categories. The starting value is $40 Million, and the cut-off liquidation value is $20 Million. New funds are allowed to enter during the simulation. Returns are adjusted for competition between categories, favorable positioning and market impact. The simulation is run for 20 years, and the last 10 years are taken for the analysis.

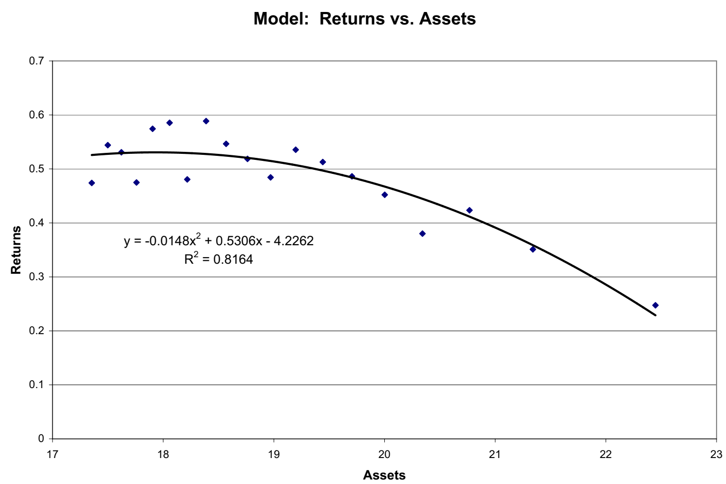

Figure 18: This figure shows the relationship between returns and assets using simulated data. Each month, returns are drawn from the Normal Distribution with μ=0.90% and the σ = 6.58%. In the beginning of the simulation, 100 funds enter into each of 10 categories. The starting value is $40 Million, and the cut-off liquidation value is $20 Million. New funds are allowed to enter during the simulation. Returns are adjusted for competition between categories, favorable positioning and market impact. The simulation is run for 50 years, and the last 10 years are taken for the analysis.

A.2 TASS Fund Category Definitions

The following is a list of category descriptions, taken directly from TASS documentation, that defines the criteria used by TASS in assigning funds in their database to one of 11 possible categories:

Convertible Arbitrage This strategy is identified by hedge investing in the convertible securities of a company. A typical investment is to be long the convertible bond and short the common stock of the same company. Positions are designed to generate profits from the fixed income security as well as the short sale of stock, while protecting principal from market moves.

Dedicated Short Bias Short biased managers take short positions in mostly equities and derivatives. The short bias of a manager's portfolio must be constantly greater than zero to be classified in this category.

Emerging Markets This strategy involves equity or fixed income investing in emerging markets around the world. As many emerging markets do not allow short selling, nor offer viable futures or other derivative products with which to hedge, emerging market investing often employs a long-only strategy.

Equity Market Neutral This investment strategy is designed to exploit equity and/or fixed income market inefficiencies and usually involves being simultaneously long and short matched market portfolios of the same size within a country. Market neutral portfolios are designed to be either beta or currency neutral, or both.

Event Driven This strategy is defined as 'special situations' investing designed to capture price movement generated by a significant pending corporate event such as a merger, corporate restructuring, liquidation, bankruptcy or reorganization. There are three popular sub-categories in event-driven strategies: risk (merger) arbitrage, distressed/high yield securities, and Regulation D.

Risk Arbitrage - This strategy is identified by managers investing simultaneously in long and short positions in both companies involved in a merger or acquisitions. Merger arbitrageurs are typically long the stock of the company being acquired and short the stock of the acquirer. The principal risk is deal risk, should the merger or acquisition fail to close.

Distressed Securities - Fund managers invest in the debt, equity or trade claims of companies in financial distress and generally bankrupt. The securities of companies in need of legal action or restructuring to revive financial stability typically trade at substantial discounts to par value and thereby attract investments when managers perceive that a turn-around will materialize.

High Yield - Often called junk bonds, this strategy refers to investing in low-grade fixed-income securities of companies that show significant upside potential. Managers generally buy and hold high yield debt.

Regulation D - This strategy refers to investments in micro and small capitalization public companies that are raising money in private capital markets. Investments usually take the form of a convertible security with an exercise price that floats or is subject to a look-back provision that insulates the investor from a decline in the price of the underlying stock.

Fixed Income Arbitrage Funds that attempt to limit volatility and generate profits from price anomalies between related fixed income securities. Most managers trade globally with a goal of generating steady returns with low volatility. This category includes interest rate swap arbitrage, United States and non-United States government bond arbitrage, forward yield curve arbitrage and mortgage-backed securities arbitrage. The mortgage-backed market is primarily United States-based and over-the-counter.

Fund of Funds A 'Multi Manager' fund will employ the services of two or more trading advisors or Hedge Funds who will be allocated cash by the Trading Manager to trade on behalf of the fund.

Global Macro Global macro managers carry long and short positions in any of the world's major capital or derivative markets. These positions reflect their views on overall market direction as influenced by major economic trends and or events. The portfolios of these funds can include stocks, bonds, currencies, and commodities in the form of cash or derivatives instruments. Most funds invest globally in both developed and emerging markets.

Long/Short Equity This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus may be regional, such as long/short US or European equity, or sector specific, such as long and short technology or healthcare stocks. Long/short equity funds tend to build and hold portfolios that are substantially more concentrated than those of traditional stock funds.

Managed Futures This strategy invests in listed financial and commodity futures markets and currency markets around the world. The managers are usually referred to as Commodity Trading Advisors, or CTAs. Trading disciplines are generally systematic or discretionary. Systematic traders tend to use price and market specific information (often technical) to make trading decisions, while discretionary managers use a judgmental approach.

Other This strategy describes hedge funds that cannot be classified in one of the ten listed categories.

References

Ackermann, C., McEnally, R. and D. Ravenscraft, 1999, "The Performance of Hedge Funds: Risk, Return, and Incentives", *Journal of Finance* 54, 833–874.

Agarwal, V. and N. Naik, 2000a, "Performance Evaluation of Hedge Funds with Buy-and-Hold and Option-Based Strategies", Hedge Fund Centre Working Paper No. HF–003, London Business School.

Agarwal, V. and N. Naik, 2000b, "On Taking the "Alternative" Route: The Risks, Rewards, and Performance Persistence of Hedge Funds", *Journal of Alternative Investments* 2, 6–23.

Agarwal, V. and N. Naik, 2000c, "Multi-Period Performance Persistence Analysis of Hedge Funds Source", *Journal of Financial and Quantitative Analysis* 35, 327–342.

Agarwal, V., Daniel, N. and N. Naik, 2003, "Flows, Performance, and Managerial Incentives in the Hedge Fund Industry", Working Paper.

Aghion, P., Dewatripont, M. and P. Rey, 1995, "Competition, Financial Discipline and Growth", mimeo, Universite Libre de Bruxelles.

Amin, G and H. Kat, 2002, "Welcome to the Dark Side: Hedge Fund Attrition and Survivorship Bias over the Period 1994-2001", Working Paper.

Bares, P., Gibson, R. and S. Gyger, 2001, "Style Consistency and Survival Probability in the Hedge Funds' Industry", Working Paper.

Baquero, G., Horst, J. and M. Verbeek, 2002, "Survival, Look-Ahead Bias and the Performance of Hedge Funds", Erasmus University Rotterdam Working Paper.

Berk, J. and R. Green, 2002, "Mutual Fund Flows and Performance in Rational Markets", Working Paper.

Brown, S. and W. Goetzmann, 2001, "Hedge Funds With Style", NBER Working Paper No. 8173.

Brown, S., Goetzmann, W., Ibbotson, R. and S. Ross, 1992, "Survivorship Bias in Performance Studies", *Review of Financial Studies* 5, 553–580.

Brown, S., Goetzmann, W. and R. Ibbotson, 1999, "Offshore Hedge Funds: Survival and Performance 1989–1995", *Journal of Business* 72, 91–118.

Brown, S., Goetzmann, W. and J. Park, 1997, "Conditions for Survival: Changing Risk and the Performance of Hedge Fund Managers and CTAs", Yale School of Management Work Paper No. F–59.

Brown, S., Goetzmann, W. and J. Park, 2000, "Hedge Funds and the Asian Currency Crisis", *Journal of Portfolio Management* 26, 95–101.

Brown, S., Goetzmann, W. and J. Park, 2001, "Careers and Survival: Competition and Risks in the Hedge Fund and CTA Industry", *Journal of Finance* 56, 1869–1886.

Brown, K., Harlow, W., and L. Starks, 1996, "Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry", *Journal of Finance* 51, 85–110.

Carpenter, J. and A. Lynch, 1999, "Survivorship Bias and Attrition Effects in Measures of Performance Persistence", *Journal of Financial Economics* 54, 337–374.

Chen, J., Hong, H., Huang, M., and J. Kubik, 2003, "Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization", Working Paper.

Chevalier, J., and G. Ellison, 1997, "Risk Taking by Mutual Funds as a Response to Incentives", *Journal of Political Economy* 105, 1167–1200.

Edwards, F., and M. Caglayan, 2001, "Hedge Fund and Commodity Fund Investments in Bull and Bear Markets", *The Journal of Portfolio Management* 27, 97–108.

Elton,E. Gruber, M. and C. Blake, 1996, "Survivorship Bias and Mutual Fund Performance", *The Review of Financial Studies* 9, 1097–1120.

Fung, W. and D. Hsieh, 1997a, "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds", *Review of Financial Studies* 10, 275–302.

Fung, W. and D. Hsieh, 1997b, "Investment Style and Survivorship Bias in the Returns of CTAs: The Information Content of Track Records", *Journal of Portfolio Management* 24, 30–41.

Fung, W. and D. Hsieh, 1999, "A Primer on Hedge Funds", *Journal of Empirical Finance* 6, 309–31.

Fung, W. and D. Hsieh, 2000, "Performance Characteristics of Hedge Funds and Commodity Funds: Natural versus Spurious Biases", *Journal of Financial and Quantitative Analysis* 35, 291–307.

Fung, W. and D. Hsieh, 2001, "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers", *Review of Financial Studies* 14, 313–341.

Getmansky, M., A. Lo, and I. Makarov, 2003, "An Econometric Model of Serial Correlation and Illiquidity In Hedge Fund Returns", *Journal of Financial Economics, forthcoming.*

Getmansky, M., 2004, "What drives hedge fund returns? Models of flows, autocorrelation, optimal size, limits to arbitrage and fund failures", unpublished Ph.D. thesis, MIT, Cambridge.

Goetzmann, W., Ingersoll, J. and S. Ross, 2003, "High Water Marks and Hedge Fund Management Contracts", *Journal of Finance* 58, 1685–1717.

Goetzmann, W., Ivkovic, Z. and G. Rouwenhorst, 1999, "Day Trading International Mutual Funds: Evidence and Policy Solutions", *Journal of Financial and Quantitative Analysis* 36, 287–309.

Goetzmann and N. Peles, 1997, "Cognitive Dissonance and Mutual Fund Investors", *Journal of Financial Research* 20, 145–158.

Gregoriou, G., 2002, "Hedge Fund Survival Lifetimes", *Journal of Asset Management* 3, 237–252.

Gruber M., 1996,"Another Puzzle: The Growth in Actively Managed Mutual Funds", *The Journal of Finance* 51, 783–810.

Ippolito R., 1992,"Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry", *Journal of Law and Economics* 35, 45–70.

Kao, D., 2002, "Battle for Alphas: Hedge Funds versus Long-Only Portfolios", *Financial Analysts Journal* 58, 16–36.

Kaplan, S. and A. Schoar, 2003, "Private Equity Performance: Returns, Persistence and Capital Flows", MIT Sloan School of Management Working Paper.

Khorana, A. and H. Servaes, 1999, "The Determinants of Mutual Fund Starts", *The Review of Financial Studies* 12, 1043–1974.

Liang, B., 1999, "On the Performance of Hedge Funds", *Financial Analysts Journal* 55, 72–85.

Liang, B., 2000, "Hedge Funds: The Living and the Dead", *Journal of Financial and Quantitative Analysis* 35, 309–326.

Liang, B., 2001, "Hedge Fund Performance: 1990–1999", *Financial Analysts Journal* 57, 11–18.

Lo, A. and C. MacKinlay, 1999, *A Non-Random Walk Down Wall Street.* Princeton, NJ: Princeton University Press.

Lochoff, R., 2002, "Hedge Funds and Hope", *The Journal of Portfolio Management* 28, 92–99.

Malkiel, B., 1995, "Returns from Investing in Equity Mutual Funds 1971 to 1991", *The Journal of Finance* 50, 549–572.

Mueller, D., 1972, "A Life Cycle Theory of the Firm", *The Journal of Industrial Economics* 20, 199–219.

Perold, A. and R. Salomon, 1994, "The Right Amount of Assets Under Management", *Financial Analysts Journal* May-June, 31–39.

Schmidt, K., 1997, "Managerial Incentives and Product Market Competition", *The Review of Economic Studies* 64, 191–213.

Sirri, E. and P. Tufano, 1998, "Costly Search and Mutual Fund Flows", *The Journal of Finance* 53, 1589–1622.

Tremont Company, distributor of TASS Database.

Vayanos,D., 2003, "Flight to Quality, Flight to Liquidity, and the Pricing of Risk", MIT Sloan School of Management Working paper.

Zheng, L., 1999, "Is Money Smart? A Study of Mutual Fund Investors' Fund Selection Ability", *The Journal of Finance* 54, 901–933.