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Three Essays on Hedge Fund Fee Structure, Return Smoothing and Gross Performance

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THREE ESSAYS ON HEDGE FUND FEE STRUCTURE, RETURN SMOOTHING AND GROSS PERFORMANCE

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To my parents, husband, and sons

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ABSTRACT

THREE ESSAYS ON HEDGE FUND FEE STRUCTURE, RETURN SMOOTHING AND GROSS PERFORMANCE

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Hedge funds feature special compensation structure compared to traditional investments. Previous studies mainly focus on the provisions and incentive structure of hedge fund contract, such as 2/20, hurdle rates, and high-water mark. The first essay develops an algorithm to empirically estimate the monthly fees, fund flows and gross asset values of individual hedge funds. We find that management fee is a major component in the dollar amount of hedge fund total fees, and fund flow is more important in determining the change in fund size compared to net returns, especially when fund is shrinking in size. We also find that best paid hedge funds concentrate in the largest hedge fund quintile. Large funds tend to perform better, earn more, and rely less on management fee for their managers' compensation. Further, we find that fund flow is an important determinant of hedge fund managerial incentives. Together

with the “visible” hands of hedge fund management, i.e. the provisions of hedge fund incentive contracts, the “invisible” hands – fund flows enable investors to effectively impact hedge fund managerial compensation and incentives.

The second essay studies the relation between return smoothing and managerial incentives of hedge funds. We use gross returns to estimate both unconditional and conditional return smoothing models. While unconditional return smoothing is a proxy of illiquidity, conditional return smoothing is related to intentional return smoothing and may be used as a first screen for hedge fund fraud. We find that return smoothing is significantly underestimated using net returns, especially for the graveyard funds. We also find that managerial incentives are positively associated with both types of return smoothing. While managers of more illiquid funds tend to earn more incentive fees, funds featuring conditional return smoothing underperform other funds and do not earn more incentive fees on average. Finally, we find that failed hedge funds feature more illiquidity and conditional return smoothing.

The third essay explores the difference between the gross-of-fee and net-of-fee hedge fund performance, by investigating the difference in distribution, factor exposures and alphas between gross returns and net returns. We find that gross returns are distributed significantly differently from net returns. The gross-of-fee alphas are higher than the net-of-fee alphas by about 4% per year on average. We also find positive relation between hedge fund performance and fund size, fund flows, and managerial incentives, which holds for both gross-of-fee performance and net-of-fee performance. Our findings suggest that it is necessary to examine the gross-of-fee performance of hedge funds separately from the net-of-fee performance, which may give us a clearer picture of the risk structure and performance of hedge fund portfolios.

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CHAPTER 1

FLOWS: THE "INVISIBLE HANDS" ON HEDGE FUND MANAGEMENT

1.1 Introduction

An important question of delegated portfolio management is whether investors are active and effective in providing ongoing economic incentives to portfolio managers. In mutual funds, performance fees are not common, and economic incentives depend implicitly on fund flows. But recent literature does not provide strong evidence that investors use fund flows effectively.[1] In particular, Sirri and Tufano (1998) find that mutual fund consumers chase returns, flocking to funds with the highest recent returns, though failing to flee from poor performers. Fund flows provide significant rewards for overperformance but do not sufficiently punish underperformance induces a convexity in the compensation schedule that impacts the manager's risk-taking incentive, but not necessarily in the best interest of the investor. Depending on past performance, it results in too much or too little risk-taking and does not result in return persistence.[2] It suggests that rents are captured by mutual fund managers while still exposing investors to moral hazard.[3] To assume that portfolio managers should act in the best interest of investors without incentives that align their interests with those of investors would be a significant act of faith, inconsistent with the vast

[1] See Brown et al. (1996), Chevalier and Ellison (1997), and Sirri and Tufano (1998).

[2] See Carpenter (2000) and Basak et al. (2007).

[3] See Berk and Green (2004).

literature on moral hazard.[4] The empirical evidence is largely consistent with the observation that economic benefits to investors, if any, are meagre.[5]

Perhaps individual investors are not best suited to monitor fund managers, and it may not be surprising that their effectiveness in setting incentives is limited. However, hedge fund investors are both large and sophisticated. Do they actively incentivize hedge fund managers, and if so, are these incentives effective? In a recent paper, Agarwal et al. (2009b) provide some of the first evidence. They document that hedge funds with greater managerial incentives, proxied by the "delta" of the option-like incentive contracts, higher level of managerial ownership, and the inclusion of high-water mark provisions in the incentive contracts, are associated with superior performance. We argue that a more complete picture is that besides the "visible hands" on hedge fund management, i.e. the compensation (incentive) contracts, fund flows also play an important role as the "invisible hands" on hedge fund management, as hedge fund managers eventually get the benefits of these contracts through fund flows.

Fees to agents like hedge funds fulfil two objectives. First, fees are designed to ensure participation by being higher than the reservation wage of the agent. Second, they provide incentives to the agent. Given the asymmetry of information and moral hazard, the incentives of the agent must be synchronized with those of the principal.

Investors in hedge funds are generally charged an annual management fee that can range anywhere from 1% to 3% of assets under management, and also an incentive fee which is typically between 15% and 25% of annual profits, based upon the funds overall performance.[6] How does such standard incentive contract of "2/20"

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[4]See Holmstrom (1979).

[5]See Elton et al. (2008).

[6]The fee structure with such rates of management fee and incentive fee is often referred to as "2/20" or "2 and 20".

in the hedge fund industry achieve these objectives optimally from the viewpoint of investors? With such a high rate of incentive fees, the pay-performance sensitivity of the hedge fund manager is higher than that of any other industry. It appears that the hedge fund contract effectively induces participation as well as provides an extremely generous pay performance sensitivity.

Assuming that the contract achieves participation, then the question arises of whether the contract is optimal from the viewpoint of investors. How do investors prevent excessive risk taking by managers? How do investors ensure that the compensation above the participation limit is not excessive? Previous literature mainly explore these questions from the "2/20" fee structure, high-water mark and other provisions of hedge fund contract such as lock-up, redemption period, and payout period. However, these explicit contract may not fully explain hedge fund compensation as the compensation also depends implicitly on the relation between fund flows and returns. How important are the explicit contract features (such as the fee rates and provisions) versus the implicit contract (i.e. the fund flows)?

The above questions were rarely discussed in literature due to the fact that net returns and net asset values are often used. Gross returns and the dollar amount of fees are rarely used due to the complexity of calculations and availability of data. With a comprehensive algorithm of gross returns and fee calculations, we are able to empirically estimate the monthly fees, fund flows, gross returns of individual hedge funds and the manager's option delta as defined by Agarwal et al. (2009b). Using Goetzmann et al. (2003) as a framework, we explore the proportion of fees in total asset values and the relative proportions of management fees and incentive fees in the total compensation. We will also examine the determinants of the change in hedge fund compensation, and how the fee structure and dollar compensations of hedge funds are related to the managerial incentives.

We find that on average management fee is a major component in hedge fund total compensation, and fund flow is more important in determining the change in fund size compared to net returns, especially when fund is shrinking in size. Our findings provide evidence that investors use fund flows to effectively limit both excessive risk taking and compensation, and that higher managerial incentives are associated with both better performance and better compensation.

The remainder of the paper is organized as follows. Section 1.2 gives a review of related literature. Section 1.3 describes the data and definition of variables used in our analysis. Section 1.4 presents the empirical analysis of fund characteristics, fees, fund flows and managerial incentives. Section 1.5 concludes the paper. The algorithm of gross returns, fees, and capital flows is given in the Appendix.

1.2 Related Literature

The incentive contract of hedge funds often feature an annual management fee at about 2% of assets, and a performance (incentive) fee at about 20% of the profits. It is also very common for hedge fund to have high-water mark and hurdle rate provisions in their fee contract. The high-water mark for each investor is the maximum share value of his or her investment in the fund. High-water mark contracts have the appealing feature that each investor only pays performance fees when the value of their investment is greater than its previous highest value, which ensures that an investor only pays an incentive fee for positive performance once any previous underperformance has been recouped. The existence of such incentive fees and high-watermark contracts means that hedge fund fees are both time-varying and path-dependent, and therefore that the relationship between gross and net of fee returns is nonlinear.

Hedge fund incentive fees can be considered a series of call options on the value of investor's investment, where the exercise price is based on the hurdle rate and the investor specific high-water mark. The option on the incentive fee is free since the manager does not have to pay for it. We can use Black-Scholes option pricing model to measure the value of the call option on incentive fees. Goetzmann et al. (2003) point out that the incentive fee contract in hedge funds provides the manager with a call option and theoretically model the value of this option. When a hedge fund receives capital flows at different points in time, the incentive fee contract resembles a portfolio of call options, where each option is related to the capital inflow at a given point in time and has its own strike price (dictated by the NAV at the time of entry and whether the fund has hurdle rate and high-water mark provisions). As Panageas and Westerfield (2009) point out, a hedge fund manager with a high-water mark provision sees a trade-off between current and future payoffs. A risky portfolio today, while increasing the probability of ending up above the high-water mark, also increases the probability that the fund falls significantly below the high-water mark. They show that with infinite horizon of high-water mark contracts, even risk-neutral managers would not place an unboundedly large weight on the risky asset, despite the option features of the contract. Following the insights of Goetzmann et al. (2003), Agarwal et al. (2009b) empirically estimate the moneyness and delta of this portfolio of call options. They find that the deltas of the portfolio of incentive contracts are better measures of managerial incentives relative to incentive fee rates.

Managerial incentives have been associated with hedge fund performance in some recent studies. Agarwal et al. (2009b) find that hedge funds with greater managerial incentives, proxied by the delta of the option-like incentive fee contracts, higher levels of managerial ownership, and the inclusion of high-water mark provisions in the incentive contracts, are associated with superior performance.

The relation between fund flow and performance for both mutual funds and hedge funds has been discussed in literature, mostly focusing on the influence of past hedge fund performance on fund flows. Gruber (1996) finds that the flow of new money into the best performing funds is much larger than the flow of money out of the poorer performing funds. Hu et al. (2009) discusses fund flows in a mutual fund setting and the relationship to risk. Hendricks et al. (1993) state that, directly or indirectly, investors in mutual funds are willing to act on such information of relative performance. Chevalier and Ellison (1997) also discuss the relationship between the inflow of assets and returns in a mutual fund setting, and Ippolito (1992) finds that mutual fund investors allocate money to funds with recent good performance. Karceski (2002) argues that mutual fund investors chase the best performing funds. Lynch and Musto (2003) discuss the asymmetric relationship between past performance and mutual fund flows, and Sirri and Tufano (1998) state that prior performance influences the flow of assets into mutual funds. Wang and Zheng (2008) indicate that hedge fund investors as a group chase past aggregate performance. Baquero and Verbeek (2009) find that money inflows are sensitive to past long-run performance and Adams (2007) examines if manager performance is driving the growth of hedge funds.

Gross returns and the dollar amount of fees are rarely explored in literature due to the complexity of calculations and lack of information. Only a few recent studies use estimated gross returns in their analysis, including Brooks et al. (2007), French (2008) and Agarwal et al. (2009b). Brooks et al. (2007) use estimated gross returns, instead of net returns in factor models, and show that the use of net of fee returns can lead to considerably biased estimates of factor exposures which can distort the picture of fund manager performance. However, their algorithm is based on single-investor assumption and fund flows are not included in their algorithm of gross return estimation. Among these papers that estimate gross returns, Agarwal et al. (2009b) provide the most comprehensive algorithm in the estimation of gross returns. They introduce an annual algorithm of incentive fees, gross returns and managerial incentive measures, which takes into account capital flows, high-water mark and hurdle rate provisions of individual investors. We will extend their algorithm by allowing monthly estimation, accrual of incentive fees before they are paid at the end of year, and modeling both management fee and incentive fee.

1.3 Data and Variable Definition

1.3.1 Data

We use the hedge fund data from Lipper TASS database. TASS has monthly net-of-fee returns, assets under management, and other fund characteristics, such as hurdle rates and high-water mark provisions, lockup, notice, and redemption periods, incentive fees, management fees, inception dates, and fund strategies. TASS also classifies hedge funds into 12 strategies: Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity Hedge, Managed Futures, Multi-Strategy, Fund of Funds, and Options Strategy. TASS reports two separate databases, one with "live" funds and another with "graveyard" funds, which keeps track of funds that stop reporting and starts in 1994. Our sample period extends from January 1994 to April 2010. We include both live and graveyard databases and focus on the post-1994 period to mitigate the potential survival-ship bias. As of April 2010, there are 14,177 hedge funds, out of which 5,989 are live, while 8,188 became graveyard during our sample period.

We exclude funds that i) report gross returns, ii) have missing information on management fee or incentive fee,[7] iii) do not report continuously and monthly, and iv) are in the categories of funds of funds, or Multi-Strategy, or managed futures, or

[7] If both rates are reported zero, then the fund is also eliminated from the sample.

option strategy, or "other" hedge funds, or have missing strategy information.[8] We delete observations that are backfilled to eliminate backfill bias.[9]

There are additional steps we take to obtain a continuous track of the assets under management (thereafter, AUM) and net asset values (thereafter, NAV) for the algorithm of gross returns and managerial incentives. We delete observations with missing or stale AUM at the beginning or the end of the fund performance history.[10]We also interpolate the missing or stale AUM for up to 3 months, and then keep the longest continuous interval of each fund. We winsorize fund flows at top and bottom 1%.[11]

After these data cleaning steps, we have 4,952 funds in our sample, out of which 3,116 are live funds and 1,836 are graveyard funds.

Assets Under Management ("EstimatedAssets" in TASS) and NAV are converted to US dollars if the original currency is not US dollar. The monthly exchange rates and the three-month LIBOR (the London Interbank Offered Rate) of US dollar are downloaded from Bloomberg.[12]

1.3.2 Variable Definition

The variables used in our analysis, especially in the algorithm of gross returns, fees and capital flows are defined as follows.

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[8]We exclude funds of funds since it has different fee structure from other fund strategies, see Brown et al. (2004). We exclude managed futures and "other" hedge funds since these categories are not usually considered "typical" hedge funds. Option strategy is newly added to the database and has only a few funds.

[9]The observation is defined as backfilled if the performance date is before "DateAddedToTass"

[10]Asset Under Management is defined as missing if it is not reported or reported as zero; it is defined as stale if it is equal to its value of previous month.

[11]As a robustness check, the unreported results show that winsorzing fund flows at 1% do not change our main findings.

[12]LIBOR is used as the hurdle rate in the calculation of fees and gross returns.

1. AUM_t, Asset Under Management, is the total value of investments managed by the fund, which is equal to NAV multiplied by the total number of shares.

2. NAV_t is the per share Net Asset Value after the deduction of all fees and expenses.

3. GAV_t, Gross Asset Value, is the end-of-month asset value per share before the deduction of all fees and expenses.

4. $HWM_{i,t}$ is the high-water mark for investor i in period t.

5. *hurdle* is an indicator variable for the hurdle rate provision, which equals 1 if the fund has a hurdle rate provision, and 0 otherwise.

6. H_t is (1 + hurdle rate). Hedge funds with hurdle rate provision do not charge a performance fee until its performance exceeds this benchmark rate.

7. $NetReturn_t$ is the monthly growth rate of the NAV in period t.

8. $GrossReturn_t$ is the monthly rate of return on GAV.

9. $Adj\_GrossReturn_t$, adjusted gross return, is the monthly rate of return on the fund value after deducting management fee, but before the deduction of incentive fees.

10. $MF\%$ is the percentage rate of management fee.

11. $IF\%$ is the percentage rate of incentive fee.

12. MF_t is the per share dollar management fee in period t, calculated as the product of $MF\%$ and NAV_{t-1}.

13. AIF_t is the per share accrued incentive fee in period t. The accrued fees earn returns for investors before being deducted from the fund at the end of each year.

14. IF_t is the per share monthly incentive fee in period t, which is the difference between current and previous accrued incentive fees. As the accrued value depends on the high-water mark and the fund's performance history, IF_t may be negative if the fund has a negative growth in that month.

15. $NShares_t$ is the total number of shares held by all investors in the fund in period t. $NShares_{i,t}$ is the number of shares held by investor i in period t.

1.4 Empirical Analysis

1.4.1 Hedge Fund Characteristics

Table 1.1 reports the descriptive statistics of fund characteristics variables for all funds and each fund strategy from January 1994 to April 2010.

The mean (median) age of funds in our sample is 5.7 (4.8) years . The size (i.e. AUM) of funds in our sample has a mean of \$118.1 million and a median of \$33.0 million.

The rate of management fee is on average 1.4%, with a median of 1.5%, while the incentive fee has a mean of 18.5% and a median of 20%. So more precisely, a common fee structure of hedge funds is about "1.5/20" for our sample.

69.9% of the hedge funds in the sample have a high-water mark provision for incentive contract. The mean and median lockup periods are both about 1 year, and the maximum lockup period is 15 years.[13]. The mean and median of redemption period are 0.3 years and 0.2 years, respectively. The percentage of funds using leverage in the sample is 63.1%, and the mean and median average leverage are 165.8 and 125.0, respectively, based on funds with non-zero leverage.

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[13]For robustness check, unreported results show that our main findings do not change if we exclude funds with lockup period of longer than two years.

The cross-sectional statistical analysis for the different strategies are reported in Panel B of Table 1.1. The results are consistent with those of all funds with some variation across different strategies. Long/Short Equity Hedge is the largest category in our sample, with about half of the funds in the sample. Convertible arbitrage is the highest in both age and fund size. As to leverage, Dedicated Short Bias, Fixed Income Arbitrage and Global Macro are highest in the proportion of leveraged funds, as well as in average leverage. Other fund characteristics have less variation across fund strategies.

1.4.2 Hedge Fund Performance: Net Return vs Gross Return

We extend the algorithm of Agarwal et al. (2009b) to empirically estimate gross returns, fees, fund flows, and manager's delta, using NAV, AUM and other fund variables. Compared to the algorithm used in Agarwal et al. (2009b), our algorithm allows the accrual of incentive fees, monthly estimation, and inclusion of management fees. Our estimation is consistent with the fact that most hedge funds charge their management fee monthly, and the incentive fees are paid annually and are accrued before paid out. Computing gross returns monthly allows us to have a larger and more accurate gross return sample, and makes the frequency of estimation match that of the reported hedge fund performance data. Estimation of management fees enables the exploration of the importance of fund flows and management fees. The details of our algorithm are given in the Appendix.

Table 1.2 summarizes the descriptive statistics of three performance measures: gross return ($GrossReturn$), adjusted gross return ($Adj\_GrossReturn$) and net return ($NetReturn$), for all funds and each fund strategy from January 1994 through April 2010.

We calculate both equally-weighted (thereafter, "EW") and value-weighted (thereafter, "VW") annualized mean return for all three performance measures. The equally-weighted mean of gross returns is 6.21% annually, which is higher than that of the adjusted gross returns by 1.42% and higher than that of the net returns by 3.80%. The value-weighted mean of gross returns is 15.03% annually, which is higher than that of the adjusted gross returns by 1.38% and higher than that of the net returns by 4.45%. The median annual gross return is 7.00%, which is higher than the median annual adjusted gross return by 1.42% and higher than the median annual net returns by 2.79%. The mean and median of returns vary across different fund strategies. For six out of eight strategies, the value-weighted mean returns are higher than the equally-weighted mean returns, implying that large funds earn higher returns compared to small funds.

All three return measures have negative skewness and positive kurtosis. The first order autocorrelation coefficient are 0.12 for all three return measures. The rejection rate of Jarque-Bera test of normality is 43.44% for gross returns, and 44.59% for net returns, implying a large portion of hedge funds feature non-normal return distribution. We also find that strategies with less liquidity, as indicated by a higher ρ_1, such as Convertible Arbitrage, Emerging Market, Event Driven, and Fixed Income Arbitrage, feature higher returns. This is associated with liquidity premium which they may earn by taking more liquidity risk.

The annualized Sharpe ratio of gross return is 0.87, which is higher than that of the adjusted gross return by 0.17, and lower than that of the net return by 0.23. The adjusted gross return has the same volatility as the gross return, but its mean is lower, as only management fee is deducted when calculating the adjusted gross returns. As a result, the adjusted gross returns have a lower Sharpe ratio than the gross returns. Net return is lower than adjusted gross return in both mean and volatility, so the result implies that the magnitude of mean dominates that of the volatility.

The results show that gross returns and net returns are different in their distributions. Therefore, the features of their difference, i.e. the fee structure of hedge funds, should be explored.

1.4.3 Hedge Fund Fees and Fund Flows

Using our algorithm, we calculate the monthly dollar amount of net flows, management fees, and incentive fees for each fund in our sample. Table 1.3 and Table 1.5 reports the descriptive statistics of fees and fund flows for all funds and for each fund strategy from January 1994 through April 2010.

In Table 1.3, statistics for both ratios and dollar amounts of hedge fund fees are reported. First, we calculate the ratio of fees relative to the fund size. On average, the total fee is 3.36% of gross asset value, with 1.38% of gross asset value as management fee, and 1.97% of the gross asset value as incentive fee. The value-weighted mean of management fee to gross asset value ratio is close to its equally weighted mean. However, the value-weighted mean of incentive fee to gross asset value ratio is 2.33%, which exceeds the corresponding equally-weighted mean by 0.36%. It implies that larger funds earn more incentive fees relative to their sizes, as they are more profitable.

As reported in Table 1.3, the average annual management fee are \$1.88 million (EW) and \$10.59 million (VW) per fund respectively, while its median is \$ 1.84 million. The average annual incentive fee per fund are \$2.81 million (EW) and \$19.56 million (VW) respectively, while its median is \$2.41 million. The average annual total fee per fund are \$4.69 million (EW) and \$ 30.15 million (VW) respectively, while its median is \$4.28 million. These results imply that large funds tend to earn more dollar fees, especially incentive fees.

In Table 1.5, we report the statistics of both the annual fund flows scaled by the previous-year-end fund size ($Flow\%$), and the dollar amount of annual fund flows. The average annual capital flow per fund is \$1.82 million (EW) and -\$45.37 million

(VW), respectively, while its median is \$2.10 million. The difference between the value-weighted and equally-weighted measures implies that large funds tend to have more outflows than smaller funds, which is consistent with what we find when we investigate the observations of fund inflows and fund outflows separately in Panel B and C of Table 1.5. When including only fund inflows, the dollar amount of fund inflow has an equally-weighted mean of \$51.69 million, and a value-weighted mean of \$177.94 million, while the median fund flow per fund per year is \$48.56 million. When including only fund outflows, the dollar amount of fund outflow has an equally-weighted mean of -\$48.20 million, and a value-weighted mean of -\$218.36 million, while the median fund flow per fund per year is -\$45.83 million. These results show that large funds experience larger amount of fund flows, especially when a fund is having outflows, compared to funds with smaller sizes.

As shown in Table 1.5, the relative size of annual fund flows (scaled by fund size) has an equally-weighted mean of 38.53%, and a value-weighted mean of only 5.61%, while its median is 25.10%. These results imply that on average, annual fund flows amount to about 39% of their previous-end-of-year asset under management. This percentage is lower for large funds, implying that the relative size of fund flows is smaller for the large funds.[14]

We also find interesting results after breaking the sample by the signs (directions) of fund flows. When funds have inflows, the relative fund flows has an equally-weighted mean of 109.24% and a value-weighted mean of 43.96%, and its median is 99.30%. These statistics imply that the average annual fund inflows tend to be about or even above the fund size, especially for small funds. However, when funds have outflows, the mean and median of the relative fund flows are -29.88% and -27.73% respectively, and the median is -29.23%. These results show that the relative size of

[14]See Fig 1.1 for a plot of the time series of average AUM.

fund outflows is much smaller than the relative size of fund inflows, and this holds for both large and small funds.

In summary, Table 1.5 imply that the relative size of annual fund flow is smaller for large funds, even though the absolute magnitude is bigger for these funds. The relative sizes of fund inflows and outflows are not symmetric. On average, hedge funds have experienced much more fund inflows than fund outflows. The relative size of annual fund inflow tend to be 100% of the previous-period fund size on average, while the average relative size of fund outflow is only about 30% of the previous fund size.

1.4.4 The Importance of Management Fees

Investors in hedge funds are generally charged an annual management fee that can range anywhere from 1% to 3% of assets under management, and also an incentive fee which is typically between 15% and 25% of annual profits, based upon the funds overall performance. However, after calculating the dollar amount of both fees, we find that management fee plays a much more important role in the hedge fund fee structure than as suggested by its percentage rate.

First, we find that management fees take a larger proportion in total compensation of hedge fund managers than incentive fees. As reported in Table 1.3, the equally-weighted (value-weighted) mean of the proportion of annual management fee in the dollar amount of annual total fee is 62.02% (54.52%). The median of the proportion of annual management fee in the dollar amount of annual total fee is 60.91%.

Also shown in Table 1.3, The management fee proportion in total fee is greater than 50% for all fund strategies, which holds for both mean and median. The proportion of management fee in the total fee varies across different fund styles. The mean ratios of management fee to the dollar amount of total fees range mostly from 50% to 70% for various hedge fund styles, while the median ratio of management fee to the dollar amount of total fees range from 55% to 75%. We also find that more liquid strategies, such as Dedicated Short Bias, Equity Market Neutral, and Global Macro, have higher proportion of management fee in total fee. This may be explained by more frequent trading of assets in these liquid strategies, which may boost up the trading costs and management fees.

The importance of management fee in total compensation is robust over time and for different fund ages. Panel A of Table 1.4 shows that this ratio increases sharply during the 1998 LTCM crisis, the 2002 internet bubble crisis, and the 2008 global financial crisis. The higher proportion of management fee in total fee during the crisis periods indicates that management fee is the major source of compensation for hedge funds when the profits and incentive fees are lower during the crisis periods. Panel B of Table 1.4 shows that the median proportion of management fee in the dollar total fee is around 50% for most fund ages.

The importance of management fee in total fees is also shown through the ratios of change in management fee to change in total fees. As reported in Table 1.3, the change in management fee amounts to 20% to 55% for all fund strategies except Dedicated Short Bias. However, this ratio is not constant over time and across fund ages.

In summary, our results imply that management fee takes a major proportion in the total compensation of hedge funds, especially during crisis periods and for liquid strategies, and its marginal contribution to the change in the total compensation is also significant.

1.4.5 Importance of Fund Flow vs. Return in Determining the Change in Fund Size

Management fee is charged as a percentage of asset under management. To further investigate the driving factors of management fees, we decompose the change in fund size into two components. The change in assets under management, i.e. the fund size, may occur in two ways. First, it may be resulted from net fund flows. Net inflows increase the fund size, while outflows reduces the fund size. Second, the change in fund size can also be attributed to the return on the existing assets under management. Mathematically, we could decompose the change in fund size as follows.

$$
\begin{aligned}
& AUM_t - AUM_{t-1} \\
= \; & [NAV_t \times NShares_t + AIF_t \times NShares_{t-1} + MVmgr_{t-1}(1 + GrossReturn_t)] \\
& -[NAV_{t-1} \times NShares_{t-1} + AIF_{t-1} \times NShares_{t-2} + MVmgr_{t-2} \\
& \times(1 + GrossReturn_{t-1})] \\
= \; & \left[NAV_t \left(NShares_{t-1} + \frac{Flow_t}{NAV_t}\right) - NAV_{t-1} \cdot NShares_{t-1}\right] \\
& + \underbrace{(AIF_t \times NShares_{t-1} - AIF_{t-1} \times NShares_{t-2})}_{A} \\
& + \underbrace{(MVmgr_{t-1}(1 + GrossReturn_t) - MVmgr_{t-2}(1 + GrossReturn_{t-1}))}_{B} \\
= \; & Flow_t + NAV_{t-1} \times NetReturn_t \times NShares_{t-1} + A + B \qquad (1.1)
\end{aligned}
$$

The first term of the above equation is the net fund flow in period t, and the second term is the earnings from the net return on existing assets of investors. The last two terms A and B are the changes in accrued incentive fees and change in market value of managers' own investment respectively, which are both determined by returns. The only variable in terms A and B is the $GrossReturn_t$, which is solved from net return and other fund parameters.[15] All other terms in item A and B are lag values, which are considered as constant. Therefore, we can simply rewrite the above equation as follows.

[15]Term A is a function of AIF_t, which is a function of $GrossReturn_t$. See equation (A.4)

$$AUM_t - AUM_{t-1} = Flow_t + f(NetReturn_t) \tag{1.2}$$

where $$f(NetReturn_t) = NAV_{t-1} \times NetReturn_t \times NShares_{t-1} + A + B \tag{1.3}$$

Using the above approach, we decompose the change in fund size (AUM) into a fund flow part and a net return part. We find that, for individual funds, the change in fund size is mostly driven by fund flow. For the median fund, net flows contribute to 71% of changes in assets under management, while only 29% of the changes in assets are resulted from the net return on existing assets. This is a strong evidence that the hedge fund compensation is mostly driven by fund flows.

We also find that this effect is not symmetric. When assets under management decrease, 98% of the decrease in the size of the median fund is resulted from net fund outflows. However, when assets under management increase, only 53% of the increase in the size of the median fund is from net fund inflows.

To further explore the driving factor of the change in fund size, we check the relative importance of fund flows by grouping yearly observations based on the sign of fund flows and the sign of change in fund size. As reported in Table 1.6, we find that in most cases, the change in fund size is consistent with the fund flows in their signs (directions). When funds increase in size, 4819 observations incur fund inflows, while only 1694 observations incur fund outflows. The consistence of signs in size changes and fund flows is more significant when funds decrease in size. In this case, 4223 observations incur fund outflows, while only 450 observations incur fund inflows. When the signs of size changes and fund flows are consistent, the mean ratio of fund flow and change in fund size of all strategies are significant at 1%.

From Table 1.6, we also find that the impact of fund flows on the change in fund size is not symmetric when fund size expands or shrink. When funds expand size with net inflows in the same year, the mean (median) ratio of fund flow to the change in fund size is 80.98% (70.92%). When funds shrink in size with net outflows in the same year, the proportion of fund flow in the change of fund size is 195.27% (102.26%). In the latter case, both mean and median are greater than 1, indicating that the size of fund outflow exceeds the change in fund size.

For observations with opposite signs of fund flow and change in fund size, the mean of the proportion of fund flow in the change of fund size is much higher than its mean, indicating that the results are mostly driven by extreme values in smaller samples. In this case, median is a more representative of the impact of the flow to the change in fund size. For observations with increase in size and fund outflows, the median is -53.77%. For observations with decrease in size and fund inflows, the median is -46.94%. Both ratios are lower in magnitude than those observations with consistent signs of flow and change in fund size.

In summary, our results show that fund flow is the driving factor of the change in fund size, and therefore of management fees. This effect is much stronger when funds shrink in size. This is an evidence that investors can use fund flows to effectively impact the compensation of hedge fund managers.

1.4.6 Hedge Fund Fee Structure and Managerial Incentives

In this section, we examine whether hedge fund managers with higher incentives, which are measured by the high-water mark provision and total delta, have different fee structure from the rest of the hedge fund sample.

Using the algorithm described in the Appendix, we empirically estimate the pay-performance sensitivity (delta) of the manager's compensation contract. As noted by Agarwal et al. (2009b) and many other papers in literature, the incentive fee contract of hedge fund manager resembles a portfolio of call options, where each option is related to the fund flow and has its own strike price which depends on the high-water mark and hurdle rate provisions of incentive contract.

We estimate three measures of managerial incentives introduced by Agarwal et al. (2009b), which are the total delta, manager's option delta, and managerial ownership. The *total delta* is the sum of manager's option delta (coming from investors' assets) and the delta from the manager's stake, which is market value of manager's investment in the fund multiplied by 0.01.[16] *Manager's option delta* is defined as the sensitivity of option value to a one percent change in asset value. *Managerial Ownership* is a fraction of the fund's total assets that corresponds to the manager's investment.

As shown in Table 1.7, the mean (median) total delta equals $0.21 million ($1.98 million). The total delta can be broken down to the manager's option delta, with a mean of $0.15 million and a median of $1.09 million, and the co-investment of managers, with a mean of 3.66% (EW) or 6.14% (VW) of total assets and a median of 2.64% of total assets. The co-investment of managers is on average $4.82 million (EW), or $73.37 (VW). These results imply that large funds have higher managerial incentives, which is consistent with the way that deltas are defined.[17]

As shown in Table 1.8, funds with higher managerial incentives, as measured by high-water mark and total delta, are paid more dollar total fees. The dollar total fees of funds with high-water mark provision is higher than other funds by about $0.8 million, in both mean and median. The impact of total delta on the total compensation is even stronger. Funds in the top quintile of total delta are paid dollar total fee at $16.8 million in mean, and $15.2 million in median, which far exceed the total compensation of the other quintiles of total delta. Our results imply that the highest compensation is concentrated in funds with the highest managerial incentives.

Table 1.8 also shows a negative relation between the managerial incentives and the percentage of management fee in total fee. For funds with high-water mark provision

[16] Agarwal et al. (2009b) assume that managers reinvest all the collected incentive fees in the fund, following the practice of industry practitioners.

[17] As shown in equation (A.1), the manager's option delta is proportional to the size of investors' assets.

and funds with higher total delta, management fee takes a lower proportion in total fee. This result is consistent with Agarwal et al. (2009b) in that funds with higher managerial incentives tend to outperform other funds. Therefore, the high-incentive funds can earn more incentive fees relative to other funds.

We find mixed results as to the relation between managerial incentives and the proportion of total fee in the gross asset value. As shown in Table 1.8, although funds with high-water mark provision earn a lower percentage of total fee, the difference is very small, only 0.14%. Total delta are positively related with the total fee percentage. The difference of the total fee percentage between the top and bottom quintiles of total delta is as much as 1%. This means that the managers' of top total delta quintile earn 1% more of the asset value in their compensation than the managers of the lowest total delta quintile. As we have mentioned earlier, the funds with the highest deltas tend to be larger funds, our results imply that the compensation of funds in the top delta quintile is higher than funds in the lowest delta quintile, even after it is scaled by the gross asset values. Considering the size of these funds in the top delta quintile, the size of the compensation difference is also economically significant.

In summary, our results support that funds with higher managerial incentives tend to have better performance as well as better compensation. Delta of incentive contracts is a good measure of managerial incentives, and has a significant impact on hedge fund fee structure. This can be explained by the fact that the magnitude of delta is determined by both incentive contract provisions and the fund size.

1.4.7 Does Size Matter for the Performance and Compensation of Hedge Fund Managers?

Our results provide evidence that fund size matters for hedge fund performance as well as the compensation of hedge fund managers. One the one hand, larger size means more management fees. Actually, as shown in Table 1.8, the total fee of funds in top AUM quintile far exceeds that of the smaller funds. The result implies that the best paid hedge funds are the ones largest in size. On the other hand, as shown in Table 1.8, hedge fund returns are also positively related with fund size. These together explain why the value-weighted fee measures are usually higher than the equally-weighted fee measures in our analysis, and why funds with higher deltas tend to be paid more.

As shown in Table 1.8, similar to the results for quintiles of deltas, the top quintile of AUM is lowest in the proportion of management fee in total fee, and the highest in the total fee percentage in gross asset value. These results support the fact that large funds tend to perform better, earn more, and rely less on management fees for their compensation.

1.5 Conclusion

In this paper, we extend the annual algorithm of empirical estimation of fees and gross returns introduced by Agarwal et al. (2009b) to a monthly algorithm which also allows the accrual of incentive fees and inclusion of management fees. Using the algorithm, we are able to explore the role of management fees and fund flows in the compensation and their relation with the incentives of hedge fund managers. From our analysis, management fee is economically important in size and can not be ignored in the analysis of hedge fund incentives. We find that on average, management fee amounts to over half of the total compensation for all hedge fund strategies. By further decomposing the change in fund size, we find that the driving force of the change in fund size, and ultimately of the management fees, is fund flows rather than net returns. We find that for median funds, net flows contribute to 71% of changes in assets under management, while only 29% of the changes in assets are resulted from the net return on existing assets. When fund is shrinking in size, this effect is more dramatic, and 98% of change in fund size is determined by fund outflows. Our results also show that funds with higher managerial incentives tend to have better performance as well as better compensation.

Our findings also shed light on the importance of fund size to the performance and compensation of hedge funds. We find that the best paid hedge funds concentrate in the top quintile of fund size. Large funds tend to perform better, earn more, and rely less on management fee for their compensation.

All the above evidences support our argument that fund flow is an important determinant of hedge fund managerial incentives. Together with the “visible” hands of hedge fund management, i.e. the provisions of hedge fund incentive contracts, the “invisible” hands– fund flows, have significant impact on hedge fund managerial compensation and incentives.

This paper provides a flexible framework for future research on the impact of fund flows on hedge fund compensations and risks, and the manager’s incentives. We can develop more studies based on our algorithm and results, and try to answer questions like: How does the proportion of incentive fees change with fund flows? How does the pay-performance sensitivity change with fund flows? More specifically, it would be interesting to see how the “active” flows could affect the performance and fees of hedge fund, where active flows are defined as fund inflow when a hedge fund does not beat its high-water mark and fund outflow when a fund beat its high-water mark. Considering our finding that 55.4% of the observations have opposite signs for fund flows and net returns, it would be interesting to see if and how the “active” flows make things different.

Table 1.1. Statistics of Fund Characteristics

In this table, we report the descriptive statistics of fund characteristics variables for all funds and for each category from January 1995 to April 2010. Panel A shows statistics for all funds, and panel B show statistics for each category. *Age* is the number of years since the inception of fund till the last available performance date. *AUM* is the yearly average of fund asset under management, reported in million US dollars. *Management Fee* and *Incentive Fee* are the percentage rates of management fee and incentive fee respectively. *High-water Mark* is an indicator variable that equals 1 for funds having a high water-mark provision, and equals 0 otherwise. *Subscription Freq* is the subscription frequency reported in years. *Lockup Period* is reported in years, and its summary statistics is based on funds that have nonzero lockup period. *Redemption Period* is the sum of Redemption Notice Period and Redemption Frequency, and it is reported in years. Leveraged is an indicator variable which is equal to 1 for funds use leverage and 0 for funds do not use leverage. *Average Leverage* is the average leverage used by the fund. In Panel B, mean of High-water Mark and Leveraged are reported, and for all other variables, median is reported. The summary statistics for average leverage is based on the subsample of funds that use leverage.

Panel A: All Funds

Variable	N	Mean	Std Dev	Min.	Median	Max.
age (year)	4952	5.7	4.0	0.3	4.8	29.6
AUM ($ million)	4952	118.1	309.4	0.0	33.0	7378.9
Management Fee (%)	4952	1.4	0.5	0.0	1.5	6.0
Incentive Fee (%)	4952	18.5	5.3	0.0	20.0	50.0
High-water Mark	4952	0.699	0.459	0.0	1.0	1.0
Subscription Frequency (year)	4763	0.1	0.1	0.0	0.1	1.0
Lockup Period (year)	1446	1.0	0.7	0.1	1.0	15.0
Redemption Period (year)	4791	0.3	0.2	0.0	0.2	2.0
Leveraged	4952	0.631	0.483	0.0	1.0	1.0
Average Leverage	1445	165.8	252.3	0.2	125.0	6000.0

Panel B: By Strategy

Strategy	N	Age (year)	AUM ($MM)	Management Fee (%)	Incentive Fee (%)	High-water Mark
Convertible Arbitrage	204	5.8	62.7	1.5	20.0	0.672
Dedicated Short Bias	38	6.2	22.0	1.2	20.0	0.632
Emerging Markets	616	4.4	31.4	1.6	20.0	0.631
Equity Market Neutral	439	3.9	27.8	1.5	20.0	0.729
Event Driven	579	5.3	55.5	1.5	20.0	0.701
Fixed Income Arbitrage	254	5.3	86.4	1.5	20.0	0.720
Global Macro	394	4.0	22.8	1.5	20.0	0.693
Long/Short Equity Hedge	2428	4.8	28.4	1.5	20.0	0.713

Strategy	N	Subscription Frequency (year)	Lockup Period (year)	Redemption Period (year)	Leveraged	Average Leverage
Convertible Arbitrage	204	0.1	1.0	0.3	0.745	200.0
Dedicated Short Bias	38	0.1	1.0	0.3	0.500	120.0
Emerging Markets	616	0.1	1.0	0.2	0.588	100.0
Equity Market Neutral	439	0.1	1.0	0.2	0.601	150.0
Event Driven	579	0.1	1.0	0.4	0.561	136.0
Fixed Income Arbitrage	254	0.1	1.0	0.2	0.787	250.0
Global Macro	394	0.1	1.0	0.2	0.761	200.0
Long/Short Equity Hedge	2428	0.1	1.0	0.2	0.618	110.0

Table 1.2. Summary Statistics: Net Return vs Gross Return

In this table we report the descriptive statistics of net return (NR), Adjusted Gross Return (Adj_GR) and Gross Return (GR) for all funds and for each category from January 1994 to April 2010. The mean, median, and standard deviation are annualized percentage based on the monthly returns of each fund. Both equally-weighted (EW) and value-weighted (VW) mean mean are reported. *Skew* measures skewness and *Kurt* measures excess kurtosis. The kurtosis reported is the excess kurtosis, i.e. the fourth moment around the mean divided by the square of the variance of the probability distribution minus 3. We also reported the first order autocorrelation coefficient (ρ_1) for funds with more than 6 observations. The Jarque-Bera statistic has an asymptotic chi-squared distribution with two degrees of freedom and can be used to test the null hypothesis that the data are from a normal distribution. We report the percentage of funds that reject the JB test at the significance level of 10%. *Sharpe* is the ratio of annualized mean return and annualized standard deviation.

Strategy	N	Variable	Ann_Mean EW	Ann_Mean VW	Ann_ Median	Ann_Std	Skew	Kurt	ρ_1	JB test (% rejection)	Sharpe
		GR	4.63	11.32	7.30	11.35	-0.60	3.82	0.33	52.45	1.26
Convertible Arbitrage	204	Adj_GR	3.24	9.87	5.91	11.35	-0.59	3.82	0.33	52.94	1.03
		NR	1.50	7.59	4.54	10.57	-0.72	4.17	0.33	53.92	0.97
		GR	1.54	3.63	-5.37	22.06	0.42	0.67	0.09	31.58	0.03
Dedicated Short Bias	38	Adj_GR	0.23	2.20	-6.68	22.06	0.42	0.67	0.09	31.58	-0.05
		NR	-2.08	0.12	-6.75	20.06	0.30	0.48	0.09	23.68	-0.14
		GR	7.37	11.55	11.30	24.77	-0.32	2.46	0.17	44.32	0.87
Emerging Markets	616	Adj_GR	5.75	9.89	9.68	24.77	-0.32	2.46	0.17	44.32	0.75
		NR	2.48	7.43	7.84	23.15	-0.44	2.71	0.17	46.75	0.63
		GR	5.75	10.46	5.96	11.26	-0.16	2.30	0.06	35.54	0.93
Equity Market Neutral	439	Adj_GR	4.38	9.23	4.58	11.26	-0.16	2.30	0.06	35.54	0.73
		NR	2.57	7.11	3.51	10.19	-0.27	2.39	0.05	38.04	0.67
		GR	7.69	13.99	8.99	11.91	-0.35	2.91	0.20	58.38	1.65
Event Driven	579	Adj_GR	6.26	12.65	7.57	11.91	-0.35	2.91	0.20	58.38	1.37
		NR	3.99	10.02	5.91	10.79	-0.48	3.26	0.19	59.07	1.32
		GR	4.89	10.35	7.67	11.93	-0.80	6.02	0.15	57.48	2.69
Fixed Income Arbitrage	254	Adj_GR	3.51	8.88	6.30	11.93	-0.80	6.02	0.15	57.09	2.29
		NR	1.68	6.58	4.91	11.06	-0.92	6.58	0.15	57.87	2.28
		GR	7.23	18.94	4.99	15.48	0.19	1.43	0.04	40.61	0.44
Global Macro	394	Adj_GR	5.64	17.55	3.40	15.48	0.19	1.43	0.04	40.61	0.27
		NR	3.48	13.75	2.39	14.02	0.10	1.41	0.04	39.34	0.21
		GR	5.83	14.85	6.05	18.86	-0.02	1.42	0.09	39.50	0.54
Long/Short Equity Hedge	2428	Adj_GR	4.47	13.67	4.70	18.86	-0.02	1.42	0.09	39.50	0.42
		NR	2.04	10.75	3.38	17.33	-0.13	1.51	0.09	40.98	0.35
		GR	6.21	15.03	7.00	17.20	-0.15	2.13	0.12	43.44	0.87
All Funds	4952	Adj_GR	4.79	13.65	5.58	17.20	-0.16	2.13	0.12	43.44	0.70
		NR	2.41	10.58	4.21	15.82	-0.27	2.30	0.12	44.69	0.64

Table 1.3. Statistics of Hedge Fund Fees of Fund Strategies

In this table, we report the descriptive statistics of fees for all funds and for each category from January 1994 to April 2010. Panel A reports the statistics of all funds, and panel B reports the statistics by strategy. *MF/GAV* is the ratio of the monthly management fee to gross asset value, annualized by multiplying by 12. *IF/GAV* is the ratio of annual incentive fee to the end-of-year gross asset value. *TotalFee/GAV* is the ratio of annual total fee to the end-of-year gross asset value. *MF/TotalFee* is the ratio of the annual management fee to the annual total fee, while $\Delta MF/\Delta TotalFee$ is the ratio of the change in annual management fee to the change in annual total fee. *MF* (*IF*) is the dollar amount of management (incentive) fee. *TotalFee* is the dollar amount of the total fee, i.e. sum of management and incentive fees. Statistics are calculated by fund, then averaged cross-sectionally. Statistics of dollar amount of fees are reported in million US dollars. Only full-year fund data are used in the calculations.

Panel A: All Funds

Variable	N	EW_Mean	VW_Mean	Std Dev	Median
MF/GAV (Ann. %)	3506	1.38	1.37	0.03	1.38
IF/GAV (Ann. %)	3506	1.97	2.33	1.96	1.76
TotalFee/GAV (Ann. %)	3506	3.36	3.70	1.93	3.15
MF/TotalFee (Ann. %)	3506	62.02	54.52	26.65	60.91
ΔMF/ΔTotalFee (Ann. %)	3506	39.32	32.84	144.90	35.24
MF ($M)	3506	1.88	10.59	0.99	1.84
IF ($M)	3506	2.81	19.56	3.07	2.41
TotalFee ($M)	3506	4.69	30.15	3.50	4.28

Panel B: By Strategy

Strategy	N	MF/GAV (Ann. %) EW_Mean	VW_Mean	Std Dev	Median	IF/GAV (Ann. %) EW_Mean	VW_Mean	Std Dev	Median
Convertible Arbitrage	153	1.39	1.41	0.03	1.39	1.58	2.01	1.48	1.41
Dedicated Short Bias	27	1.35	1.43	0.05	1.36	1.76	1.69	2.46	1.45
Emerging Markets	432	1.58	1.63	0.07	1.58	2.65	2.05	2.81	2.39
Equity Market Neutral	295	1.36	1.23	0.02	1.36	1.26	1.76	1.25	1.15
Event Driven	412	1.39	1.31	0.03	1.39	2.00	2.48	1.67	1.85
Fixed Income Arbitrage	179	1.35	1.47	0.02	1.35	1.66	2.02	1.43	1.51
Global Macro	270	1.56	1.44	0.03	1.56	1.71	2.18	1.74	1.57
Long/Short Equity Hedge	1738	1.32	1.16	0.03	1.32	2.03	2.48	2.08	1.78

Strategy	N	MF/TotalFee (Ann. %) EW_Mean	VW_Mean	Std Dev	Median	ΔMF/ΔTotalFee (Ann. %) EW_Mean	VW_Mean	Std Dev	Median
Convertible Arbitrage	153	62.90	55.07	26.94	61.37	41.99	21.94	166.53	37.12
Dedicated Short Bias	27	71.73	68.21	34.22	75.08	-32.08	11.53	127.78	-0.20
Emerging Markets	432	63.01	68.78	29.58	61.65	20.47	54.66	190.26	-8.00
Equity Market Neutral	295	69.15	65.15	24.17	68.88	52.08	49.72	162.80	49.89
Event Driven	412	57.68	44.66	24.41	55.40	41.94	33.19	141.56	36.41
Fixed Income Arbitrage	179	60.80	54.10	23.87	60.15	42.61	47.98	209.53	37.29
Global Macro	270	65.45	56.67	23.97	64.38	57.08	26.02	116.31	46.61
Long/Short Equity Hedge	1738	60.97	54.90	27.45	59.96	39.25	7.16	126.60	41.30

Panel B: By Strategy (Continued)

Strategy	N	MF ($M) EW_Mean	VW_Mean	Std Dev	Median	IF ($M) EW_Mean	VW_Mean	Std Dev	Median
Convertible Arbitrage	153	2.88	15.38	1.13	2.84	3.69	25.02	4.00	2.99
Dedicated Short Bias	27	0.52	0.93	0.24	0.50	0.84	0.98	0.96	0.68
Emerging Markets	432	1.66	7.58	0.96	1.59	2.55	8.43	2.98	2.19
Equity Market Neutral	295	1.24	6.40	0.50	1.22	1.09	3.22	1.08	1.02
Event Driven	412	3.71	15.59	1.95	3.58	5.93	27.18	5.14	5.36
Fixed Income Arbitrage	179	2.88	8.08	1.35	2.85	3.48	9.74	3.24	2.90
Global Macro	270	2.06	13.54	1.92	1.92	2.98	20.62	5.43	2.11
Long/Short Equity Hedge	1738	1.42	5.88	0.69	1.40	2.28	13.27	2.55	1.98

Strategy	N	TotalFee/GAV (Ann. %) EW_Mean	VW_Mean	Std Dev	Median	TotalFee ($M) EW_Mean	VW_Mean	Std Dev	Median
Convertible Arbitrage	153	2.98	3.42	1.46	2.80	6.58	40.40	4.12	5.85
Dedicated Short Bias	27	3.11	3.12	2.43	2.81	1.36	1.91	1.09	1.25
Emerging Markets	432	4.23	3.68	2.76	3.97	4.22	16.02	3.43	3.80
Equity Market Neutral	295	2.61	2.99	1.24	2.50	2.33	9.62	1.34	2.27
Event Driven	412	3.39	3.79	1.65	3.24	9.64	42.77	5.98	9.01
Fixed Income Arbitrage	179	3.01	3.49	1.41	2.86	6.36	17.82	3.98	5.84
Global Macro	270	3.26	3.62	1.72	3.13	5.03	34.16	6.52	4.24
Long/Short Equity Hedge	1738	3.35	3.64	2.05	3.10	3.70	19.15	2.82	3.38

Table 1.4. Management Fee Ratios Over Time and For Different Fund Ages

In this table, we report the descriptive statistics of fees from January 1994 to April 2010. Panel A reports the time-series statistics of all funds, and panel B reports the statistics by fund age. *MF/GAV* is the ratio of the monthly management fee to gross asset value, annualized by multiplying by 12. *MF/TotalFee* is the ratio of the annual management fee to the annual total fee, while Δ*MF/*Δ*TotalFee* is the ratio of the change in annual management fee to the change in annual total fee. Statistics are calculated by fund, then averaged cross-sectionally. Only full-year fund data are used in the calculations. Statistics of funds with ages older than 16 years are not reported, as only less than 70 funds are in this sample.

Panel A: Management Fee Ratios Over Time

Year	N	MF/TotalFee (Ann. %)			ΔMF/ΔTotalFee (Ann. %)		
		Mean	Median	Std Dev	Mean	Median	Std Dev
1994	2	37.85	37.85	20.85			
1995	10	57.70	45.99	37.77	66.08	66.08	64.95
1996	82	48.11	32.51	34.66	30.79	18.88	43.70
1997	176	52.42	38.01	35.26	1.51	14.63	248.81
1998	265	68.04	80.21	34.78	62.56	6.57	324.97
1999	373	41.44	27.85	35.16	30.43	4.63	227.68
2000	450	62.54	59.64	34.84	36.62	1.24	386.15
2001	596	64.88	65.73	31.71	65.49	19.95	275.30
2002	814	71.70	89.58	31.31	71.88	25.96	669.85
2003	956	43.46	32.74	30.51	33.20	6.35	391.61
2004	1056	53.14	44.79	29.70	47.60	14.42	872.97
2005	1181	57.67	51.73	29.73	-28.33	14.13	951.95
2006	1353	46.70	37.37	27.87	11.43	11.36	275.59
2007	1238	52.91	45.02	30.69	47.33	7.23	635.46
2008	1253	87.79	100.00	24.36	22.69	6.17	260.50
2009	1427	60.74	60.93	33.60	40.58	25.84	458.76

Panel B: Management Fee Ratios Of Different Fund Ages

Age	N	MF/TotalFee (Ann. %) Mean	Median	Std Dev	ΔMF/ΔTotalFee (Ann. %) Mean	Median	Std Dev
2	1069	55.47	48.20	32.84			
3	1604	56.84	50.23	32.83	59.03	14.87	888.49
4	1597	59.37	55.23	32.94	61.07	10.69	662.73
5	1441	60.57	57.38	33.01	12.62	11.33	308.02
6	1124	60.76	57.07	32.65	20.23	11.93	352.78
7	907	58.79	52.17	32.99	26.98	7.12	431.05
8	770	59.79	54.30	33.51	58.19	12.12	633.28
9	630	59.44	52.79	32.67	38.03	9.05	448.50
10	494	61.65	57.69	33.29	15.82	9.41	170.70
11	411	59.42	53.10	33.27	29.91	12.33	113.35
12	316	61.94	60.03	33.59	19.96	10.17	126.33
13	248	63.61	64.70	34.55	11.97	10.09	296.25
14	174	55.59	48.85	34.38	34.85	8.08	177.14
15	132	57.18	49.72	34.05	32.96	3.71	363.98
16	106	61.57	60.77	35.52	-253.30	10.38	2700.82

Table 1.5. Statistics of Hedge Fund Flows

In this table, we report the summary statistics of flows for all funds and for each category from January 1994 to April 2010. Panel A reports the statistics of fund flows, by including both inflows and outflows in the calculation. Panel B reports the statistics of fund flows, by including only inflows in the calculation. Penal C reports statistics of fund flows, by including only outflows in the calculation. Flow (Ann. %) is the annual net fund flow scaled by the previous-end-of-year AUM. Flow ($M) is the dollar amount of annual capital flows per fund, reported in million US dollars. Only full-year fund data are used in the calculation of the statistics.

Panel A: Statistics of Fund Flows, Including Both Inflows and Outflows

Strategy	N	Flow (Ann. %)				Flow ($M)			
		EW_Mean	VW_Mean	Std Dev	Median	EW_Mean	VW_Mean	Std Dev	Median
Convertible Arbitrage	152	26.37	11.79	88.48	8.50	1.13	2.00	89.04	2.06
Dedicated Short Bias	27	23.63	4.74	89.50	1.31	-0.16	-8.88	19.79	-0.71
Emerging Markets	432	34.16	5.13	70.25	23.98	-3.74	8.65	43.74	-4.72
Equity Market Neutral	295	41.55	35.82	96.01	29.48	0.28	9.01	40.52	1.86
Event Driven	412	42.00	23.41	87.38	24.20	26.79	74.12	88.18	25.89
Fixed Income Arbitrage	179	26.05	16.60	97.81	10.27	-0.46	-1.71	95.28	-0.52
Global Macro	269	54.47	6.72	141.63	33.88	10.37	-69.33	104.98	7.65
Long/Short Equity Hedge	1737	38.39	3.39	88.50	26.83	-3.46	-48.63	51.25	-2.34
All Funds	4949	38.53	5.61	90.62	25.10	1.82	-45.37	61.21	2.10

Panel B: Statistics of Fund Flows, Including Inflows Only

Strategy	N	Flow (Ann. %)				Flow ($M)			
		EW_Mean	VW_Mean	Std Dev	Median	EW_Mean	VW_Mean	Std Dev	Median
Convertible Arbitrage	122	105.14	40.91	93.54	98.86	69.45	182.82	43.15	67.94
Dedicated Short Bias	21	86.66	82.13	103.89	60.88	15.59	16.54	15.13	13.41
Emerging Markets	278	115.75	43.88	86.92	111.77	38.05	111.74	31.24	35.47
Equity Market Neutral	227	109.29	65.77	115.39	102.40	31.78	90.53	28.69	30.61
Event Driven	316	116.75	47.67	104.57	107.57	87.38	283.06	71.35	80.39
Fixed Income Arbitrage	124	101.68	53.92	131.38	80.72	80.45	154.31	83.25	75.80
Global Macro	183	158.95	67.27	220.04	146.94	78.85	287.76	84.31	72.47
Long/Short Equity Hedge	1220	99.91	38.47	100.74	89.19	41.11	100.33	28.76	38.96
All Funds	2491	109.24	43.96	110.05	99.30	51.69	177.94	42.49	48.56

Panel C: Statistics of Fund Flows, Including Outflows Only

Strategy	N	Flow (Ann. %)				Flow ($M)			
		EW_Mean	VW_Mean	Std Dev	Median	EW_Mean	VW_Mean	Std Dev	Median
Convertible Arbitrage	136	-30.50	-24.07	17.78	-30.42	-68.71	-134.58	32.41	-67.21
Dedicated Short Bias	21	-36.61	-38.56	18.57	-37.25	-18.78	-30.68	10.51	-18.65
Emerging Markets	349	-29.92	-24.15	19.35	-28.93	-33.49	-77.39	22.76	-32.02
Equity Market Neutral	220	-33.66	-25.88	19.63	-33.31	-35.81	-71.60	25.15	-33.87
Event Driven	305	-27.34	-21.14	16.74	-26.35	-63.50	-160.01	37.33	-60.59
Fixed Income Arbitrage	145	-31.63	-30.58	20.61	-31.18	-79.50	-147.99	57.47	-77.00
Global Macro	189	-34.76	-32.57	21.11	-34.14	-56.70	-286.49	77.11	-49.69
Long/Short Equity Hedge	1337	-28.78	-27.33	16.19	-28.13	-44.37	-139.79	41.72	-42.36
All Funds	2702	-29.88	-27.73	17.55	-29.23	-48.20	-218.36	39.40	-45.83

Table 1.6. Decomposition of the Change in Fund Size

In this table, we report the summary statistics of the ratio of annual fund flow and annual change in AUM, as given by equation (1), for all funds and for each category from January 1994 to April 2010. Panel A (B) reports statistics when both the sign of fund flow and change in AUM are positive (negative). Panel C (D) reports statistics based on observations when fund inflow (outflow) occurs while there is an decrease (increase) in AUM. The mean and median statistics are reported in percentage. Only full-year observations with non-zero flow and AUM are used in the calculation of the statistics.

Panel A: Sign(ΔAUM) = Sign(Flow) = 1

PrimaryCategory	N	Flow/ΔAUM Mean	Median	t-stat	Prob(t)
Convertible Arbitrage	248	76.05	80.39	36.63	0.00
Dedicated Short Bias	44	231.88	86.63	2.59	0.01
Emerging Markets	459	74.82	59.54	11.97	0.00
Equity Market Neutral	408	83.60	81.10	26.37	0.00
Event Driven	758	77.72	71.87	22.02	0.00
Fixed Income Arbitrage	278	71.92	74.20	30.09	0.00
Global Macro	339	94.70	79.91	10.82	0.00
Long/Short Equity Hedge	2285	79.52	66.98	29.79	0.00
All Funds	4819	80.98	70.92	43.63	0.00

Panel B: Sign(ΔAUM) = Sign(Flow) = -1

PrimaryCategory	N	Flow/ΔAUM Mean	Median	t-stat	Prob(t)
Convertible Arbitrage	242	243.17	106.04	5.40	0.00
Dedicated Short Bias	35	115.74	85.80	4.78	0.00
Emerging Markets	468	190.68	94.76	7.82	0.00
Equity Market Neutral	363	146.14	103.90	12.69	0.00
Event Driven	512	176.82	106.89	11.40	0.00
Fixed Income Arbitrage	241	200.26	112.95	8.21	0.00
Global Macro	271	169.60	101.96	10.62	0.00
Long/Short Equity Hedge	2091	207.89	99.33	9.80	0.00
All Funds	4223	195.27	102.26	17.00	0.00

Panel C: Sign(ΔAUM) = 1; Sign(Flow) = -1

PrimaryCategory	N	Flow/ΔAUM Mean	Median	t-stat	Prob(t)
Convertible Arbitrage	72	-580.95	-73.85	-1.37	0.17
Dedicated Short Bias	6	-160.64	-82.41	-2.32	0.07
Emerging Markets	313	-323.89	-40.95	-4.38	0.00
Equity Market Neutral	96	-272.83	-42.27	-3.59	0.00
Event Driven	208	-331.60	-70.79	-6.23	0.00
Fixed Income Arbitrage	69	-281.93	-68.77	-4.02	0.00
Global Macro	84	-610.58	-52.27	-1.27	0.21
Long/Short Equity Hedge	846	-379.17	-53.85	-3.34	0.00
All Funds	1694	-372.41	-53.77	-5.64	0.00

Panel D: Sign(ΔAUM) = - 1; Sign(Flow) = 1

PrimaryCategory	N	Flow/ΔAUM Mean	Median	t-stat	Prob(t)
Convertible Arbitrage	15	-4618.08	-105.92	-1.03	0.32
Dedicated Short Bias	9	-134.05	-52.60	-1.97	0.08
Emerging Markets	86	-104.97	-39.02	-5.03	0.00
Equity Market Neutral	27	-129.33	-29.78	-2.83	0.01
Event Driven	31	-153.89	-52.85	-3.19	0.00
Fixed Income Arbitrage	17	-77.56	-30.21	-2.88	0.01
Global Macro	15	-109.07	-33.73	-2.22	0.04
Long/Short Equity Hedge	250	-581.53	-56.20	-1.98	0.05
All Funds	450	-524.68	-46.94	-2.37	0.02

Table 1.7. Statistics of Hedge Fund Managerial Incentives

In this table, we report the summary statistics of hedge fund managerial incentive measures for all funds and for each category from January 1994 to April 2010. Panel A reports the statistics for all funds, and panel B reports the statistics by strategy. Total Delta is the total expected dollar change in the manager's wealth for a 1% change in NAV. Manager's Option Delta is the delta from investors' assets. Managerial ownership is the ratio of manager's investment in the fund to the total asset under management. MV_mgr is the dollar amount of manager's own investment in the fund. Full year data is used for the calculations. Statistics of deltas and MV_mgr are reported in million US dollars.

Panel A: All Funds

Variable	N	EW_Mean	VW_Mean	StdDev	Median
Total Delta ($M)	4277	0.21	1.98	0.15	0.20
Manager's Option Delta ($M)	4277	0.15	1.09	0.10	0.14
Managerial Ownership (%)	4952	3.66	6.14	3.64	2.64
MV_mgr ($M)	4952	4.82	73.37	4.13	4.08

Panel B: By Strategy

Strategy	N	Total Delta ($M) EW_Mean	VW_Mean	Std Dev	Median	Manager's Option Delta ($M) EW_Mean	VW_Mean	Std Dev	Median
Convertible Arbitrage	173	0.32	2.37	0.17	0.31	0.24	1.68	0.13	0.23
Dedicated Short Bias	35	0.04	0.08	0.03	0.04	0.03	0.06	0.02	0.03
Emerging Markets	531	0.17	0.76	0.13	0.15	0.10	0.39	0.07	0.09
Equity Market Neutral	373	0.11	0.59	0.06	0.11	0.09	0.47	0.05	0.08
Event Driven	487	0.40	2.63	0.30	0.36	0.28	1.55	0.20	0.26
Fixed Income Arbitrage	228	0.33	1.12	0.20	0.32	0.24	0.72	0.15	0.23
Global Macro	336	0.26	2.85	0.18	0.24	0.16	1.24	0.11	0.14
Long/Short Equity Hedge	2119	0.18	1.15	0.11	0.16	0.12	0.69	0.08	0.11

Strategy	N	Managerial Ownership (%) EW_Mean	VW_Mean	Std Dev	Median	MV_mgr ($M) EW_Mean	VW_Mean	Std Dev	Median
Convertible Arbitrage	204	3.65	3.44	3.98	2.49	4.93	43.42	4.13	4.49
Dedicated Short Bias	38	4.28	4.70	4.47	2.19	1.05	2.09	0.92	0.79
Emerging Markets	616	4.59	5.56	4.48	3.25	4.84	29.75	4.53	3.84
Equity Market Neutral	439	2.47	2.70	2.58	1.87	1.63	7.20	1.26	1.50
Event Driven	579	3.02	4.05	2.95	2.34	7.84	103.36	7.38	5.99
Fixed Income Arbitrage	254	3.60	5.70	3.98	2.37	7.00	38.24	5.71	6.04
Global Macro	394	3.55	10.93	3.64	2.46	7.43	140.21	6.13	6.88
Long/Short Equity Hedge	2428	3.82	5.66	3.71	2.76	4.06	40.22	3.33	3.52

Table 1.8. Subgroup Analysis of Hedge Fund Fees

In this table, we report the descriptive statistics of fees for subgroups of HighWaterMark provision, total delta and fund size, from January 1994 to April 2010. Panel A reports the statistics of fees for subgroups by high-water mark provision, panel B reports the statistics of fees for quintiles of total delta, and panel C reports statistics of fees for quintiles of average assets under management. Variables are defined in Table 1.3. N is the number of funds in each subgroup. Statistics are calculated by fund, then averaged cross-sectionally. Statistics of dollar amount of fees are reported in million US dollars. Only full-year fund data are used in the calculations.

Panel A: Statistics of Fees for Subgroups of HighWaterMark

HighWaterMark	N	TotalFee ($M)			MF/TotalFee (Ann. %)			TotalFee/GAV (Ann. %)			Gross Return (Ann. %)		
		Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
1	2486	4.94	4.52	3.52	61.40	60.21	26.54	3.32	3.12	1.80	7.62	8.10	15.82
0	1020	4.09	3.72	3.42	63.54	62.62	26.97	3.46	3.21	2.28	2.95	4.44	20.39

Panel B: Statistics of Fees for Subgroups of Total Delta Quintiles

Total Delta	N	TotalFee ($M)			MF/TotalFee (Ann. %)			TotalFee/GAV (Ann. %)			Gross Return (Ann. %)		
		Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Highest	773	16.80	15.22	10.51	51.60	48.06	27.18	4.03	3.76	2.21	14.44	14.71	14.64
1	717	2.75	2.57	1.64	58.83	57.51	28.37	3.47	3.22	1.92	11.56	11.98	15.25
2	699	1.19	1.12	0.67	60.61	59.78	28.03	3.43	3.23	1.91	9.08	10.04	16.95
3	620	0.46	0.44	0.26	64.11	64.32	27.47	3.15	2.96	1.92	7.69	7.37	18.31
Lowest	537	0.13	0.13	0.06	69.36	69.80	24.86	2.94	2.78	1.77	0.74	1.49	21.24

Panel C: Statistics of Fees for Subgroups of AUM Quintiles

AUM	N	TotalFee ($M)			MF/TotalFee (Ann. %)			TotalFee/GAV (Ann. %)			Gross Return (Ann. %)		
		Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Highest	819	16.31	14.86	10.47	55.98	53.10	26.20	3.74	3.54	1.99	10.80	12.16	14.78
1	789	2.56	2.36	1.76	61.64	60.31	27.38	3.26	3.04	1.84	9.63	10.82	15.91
2	726	1.02	0.94	0.72	64.35	63.98	27.19	3.23	2.99	1.93	5.25	6.20	16.47
3	655	0.42	0.39	0.28	64.63	64.04	25.86	3.18	3.02	1.82	5.04	5.76	18.35
Lowest	517	0.10	0.10	0.08	65.59	65.90	26.39	3.30	3.09	2.14	0.33	0.07	20.49

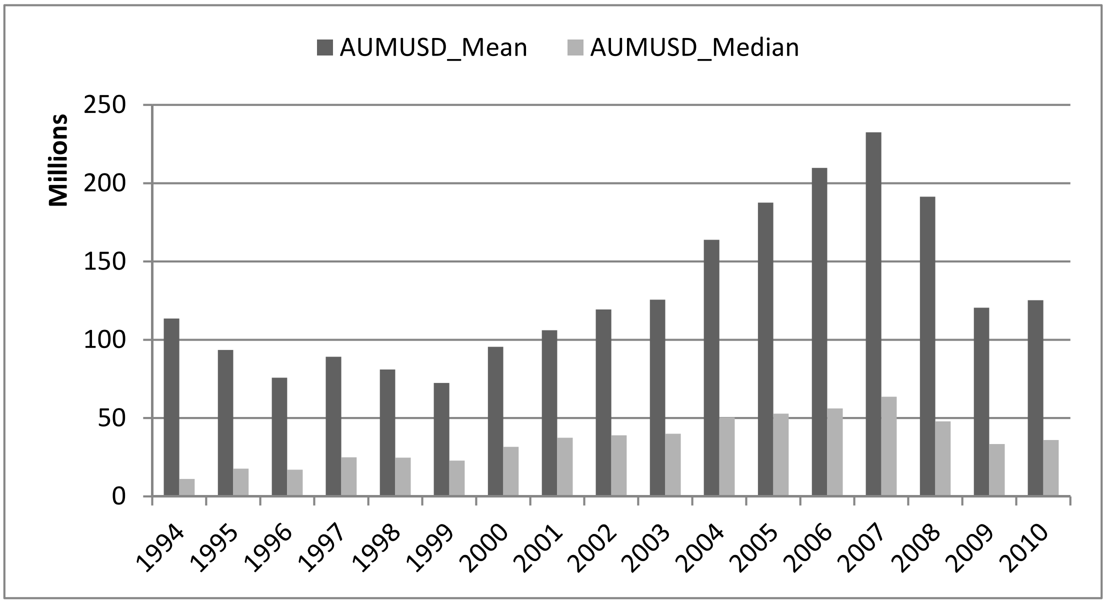

Figure 1.1. Average AUM Over Time

CHAPTER 2

RETURN SMOOTHING, MANAGERIAL INCENTIVES, AND HEDGE FUND FAILURES

2.1 Introduction

The hedge fund industry has grown dramatically in the past decades, and gained popularity among institutional investors due to limited regulatory oversight, advantageous fee structures, and the flexibility in investment strategies.

Hedge fund returns are often highly serially correlated. Getmansky et al. (2004a) document an average serial correlation of 12.1% for reported monthly hedge fund returns. The serial correlation in hedge fund returns could also bias the risk-adjusted return measures, such as the Sharpe ratio. Lo (2002) finds that annualized Sharpe ratios can be overstated dramatically (up to 65%) due to the presence of serial correlation in the monthly returns of hedge funds. Moreover, spurious serial correlation can lead to wealth transfers between new, existing, and departing investors.[1]

As suggested by Getmansky et al. (2004a), serial correlation could be a proxy of illiquidity in hedge fund investments. Share restrictions for fund withdrawal, such as lockup period and redemption period, are common among hedge funds. These share restrictions discourage capital withdrawal of investors and allow managers to have the discretion to invest in illiquid assets more easily. These share restrictions have impacts on the performance of hedge funds, as well as their flow-performance relations. Aragon (2007) finds that the excess returns of funds with lockup restrictions are approximately 4-7% per year higher than those of nonlockup funds. Ding et al. (2009) find that

[1] See Boudoukh et al. (2002) and Cumming and Dai (2010).

individual hedge funds exhibit different flow-performance relationships, depending on the presence of share restrictions.

Intentional return smoothing is also a possible explanation for the high serial correlation in hedge fund returns. The special fee structure and the lack of transparency allow the possibility that hedge fund managers may misreport their returns in order to charge more fees. Intentional return smoothing is possible if there is some flexibility on the valuation of the assets traded by the funds. Misreporting of hedge fund returns has been observed and analyzed in recent studies, including Agarwal et al. (2009a), Bollen and Pool (2009), and Cumming and Dai (2010). Due to the lack of information, it is hard to disentangle discretionary return smoothing from illiquidity as causes of serial correlation in returns. A few recent studies address this question in different aspects. Bollen and Pool (2008) try to distinguish purposeful managerial smoothing from innocuous causes of serial correlation by applying a model of conditional return smoothing. They show that if true returns are independently distributed and a manager fully reports gains but delays reporting losses, then reported returns will feature conditional serial correlation. Agarwal et al. (2009a) find spikes of returns in December for hedge funds with greater incentives and greater opportunities to inflate returns, which suggests that hedge funds manage their returns upwards in an opportunistic fashion in order to earn higher fees. In this paper, we are interested to see if managerial incentives are driving return smoothing. We will also explore the illiquidity and return smoothing properties of failed hedge funds.

The compensation of hedge fund managers often features an asymmetric fee structure. Hedge fund investors are generally charged an annual management fee that can range anywhere from 1% to 3% of assets under management, and also an incentive fee which is typically between 15% and 25% of annual profits, based upon the fund's overall performance. The high-water mark for each investor is the maximum share value since his or her initial investment in the fund. High-water mark contracts have the appealing feature that each investor only pays performance fees when the value of their investment is greater than its previous highest value, which ensures that an investor only pays an incentive fee for positive performance once any previous underperformance has been recouped.

Higher incentive fees and high-water mark provisions have been associated with better performance of hedge funds (See Liang (1999), Ackermann et al. (1999), etc.). A few recent papers explore the impact of other measures of managerial incentives on the performance and management of hedge funds. Agarwal et al. (2009b) use the delta of the option-like incentive fee contracts, higher levels of managerial ownership, and the inclusion of high-water mark provisions in the incentive contracts as measures of managerial incentives. They find that hedge fund managerial incentives are associated with superior performance. Agarwal et al. (2009a) find that funds with greater managerial incentives exhibit more December return spikes, which is an indicator of managed returns in hedge funds. However, none of these studies explore the relation between managerial incentives and serial correlation of fund returns. In this paper, we will examine if the return smoothing of hedge funds is related to managerial incentives.

We argue that gross returns should be used for the study of return smoothing. One reason is that gross returns are more relevant to the process and causes of return smoothing. The risk management and return smoothing of hedge fund managers are directly related to the performance of hedge funds gross of all fees. Specifically, the valuation of (illiquid) assets and intentional returns smoothing both take place before the calculation and deduction of fees. So gross returns provide a clearer picture of hedge fund liquidity and they are also more appropriate for the estimation of return smoothing. However, due to the availability of data and the complexity of calculation, most studies of hedge funds in literature use net returns and net asset values in their analysis. Gross returns are rarely used in previous studies. For the estimation of gross returns and measures of managerial incentives, we follow the monthly algorithm of Feng et al. (2010), which is an extended version of Agarwal et al. (2009b) that allows accrual of incentive fees, monthly estimation, and inclusion of management fees.

Another reason that gross returns should be used for the studies of return smoothing is that the asymmetric structure of fees results in the difference between the distribution of gross returns and that of net returns. Unlike mutual funds, the gross return of hedge funds is not just a percentage of net returns, but bears a more complex distributional feature. As shown in the later part of this paper, statistics such as the mean, standard deviation, skewness and kurtosis are all different between gross returns and net returns. For the majority of funds in the sample, the difference between statistics of these two return measures is significant. Therefore, it is important to examine the properties of gross returns separately from net returns for the studies of return smoothing and other gross-of-fee properties of fund performance.

In this paper, we examine if the estimated return smoothing profile and smoothing-adjusted Sharpe ratio using gross returns are significantly different from those using net returns. We also analyze the impacts of managerial incentives on the unconditional and conditional return smoothing of hedge funds, and examine if the managers of hedge funds with more return smoothing earn more incentive fees. Finally, we explore the return smoothing properties of the failed hedge funds, where the failure of hedge funds is defined using performance measures.

This paper contributes to the literature in several ways. It is the first study to use gross returns in the estimation of the unconditional and conditional return smoothing models. This paper is also the first paper to examine the relationship between managerial incentives and return smoothing, and the dollar amount of fees charged by managers with different smoothing properties. We also add to the literature of hedge fund failures by linking return smoothing to the failures of hedge funds.

The rest of the paper is organized as follows. Section 2.2 gives a review of related literature. Section 2.3 describes the data. Section 2.4 introduces the return smoothing models used in the paper. Section 2.5 presents the empirical analysis of return smoothing. Section 2.6 concludes the paper. The algorithm of gross returns and deltas is provided in the Appendix.

2.2 Literature Review

Recent literature studies the liquidity of hedge fund investment and observes serial correlation in hedge fund returns. Getmansky et al. (2004a) document substantial positive serial correlation in reported monthly hedge fund returns with an average level of 12.1% for a sample of 909 hedge funds in the TASS Hedge Fund database after applying a filter of 5-year continuous life. Various sources of serial correlation have been examined in Getmansky et al. (2004a) including time-varying expected returns, time-varying leverage, and marking illiquid assets to market using extrapolation. They find that the most likely explanation is illiquidity exposure and smoothed returns. Li and Patton (2007) find evidence of time variation in the degree of liquidity of hedge fund investments. They find hedge funds in equity-based styles exhibit decreases in liquidity when stock market returns are low and bond market returns are high. In contrast, hedge funds in fixed income styles exhibit lower liquidity when equity market volatility is high, and when the fund experiences inflows or outflows of funds.

As pointed out by Getmansky et al. (2004a), serial correlation can be caused by purposeful managerial smoothing of contemporaneous and lagged asset returns. Bollen and Pool (2008) try to distinguish purposeful managerial smoothing from innocuous causes of serial correlation by applying a model of conditional return smoothing. They use conditional serial correlation as a measure of conditional return smoothing, and show that if true returns are independently distributed and a manager fully reports gains but delays reporting losses, then reported returns will feature conditional serial correlation. Bollen and Pool (2008) use a logit regression to model the relationship between conditional return smoothing and fund flows, and find that the probability of observing conditional serial correlation is positively related to the volatility of investor cash flows and negatively related to the magnitude of investor cash flows, which provides evidence that conditional smoothing may happen in response to the risk of capital flight.

The illiquidity and smoothed returns may bias the risk-adjusted performance measures. Asness et al. (2001) note that illiquid assets held by hedge funds can lead to changes in hedge fund values that are non-synchronous with changes in common benchmarks. If reported hedge fund values are stale, traditional estimates of volatility and correlation with benchmarks can be biased downward, thereby improving the risk-adjusted performance of the funds. Lo (2002) finds that annualized Sharpe ratio can be overstated dramatically (up to 65%) due to presence of serial correlation in the monthly returns of hedge funds. Smoothing-adjusted Sharpe ratio is introduced by Lo (2002), and Getmansky et al. (2004a) introduce estimator of smoothing-adjusted Sharpe ratio for small samples.

To enable managers to have more discretion of investing in illiquid assets, hedge funds often have share restrictions on fund withdrawal such as lockup period and redemption period. Aragon (2004) finds that the excess returns of funds with lockup restrictions are approximately 4-7% per year higher than those of nonlockup funds. He also finds that restrictions on shareholder activity are more common in younger hedge funds and are positively related to the level of smoothing. He suggests that share restrictions allow funds to effectively manage illiquid assets, and these benefits are captured by investors as a share illiquidity premium. Ding et al. (2009) find that the convexity of flow-performance relation varies with the share restrictions. Hedge funds exhibit a convex flow performance relation in the absence of share restrictions, but exhibit a concave relation in the presence of restrictions. They argue that this is resulted from both the direct effect and the indirect effect of the binding restrictions, as investors may endogenize expected future binding restrictions when investing their money. They also find that live funds exhibit a concave flow-performance relation due to stricter flow restrictions than defunct funds, which display a convex relation.

As pointed out by Lo (2001), for portfolios of illiquid securities, i.e., securities that are not frequently traded and for which there may not be a well-established market price, a hedge-fund manager has considerable discretion in marking the portfolio's value at the end of each month to arrive at the fund's net asset value (NAV). Given the nature of hedge-fund compensation contracts and performance statistics, managers have incentives to "smooth" their returns by marking their portfolios to less than their actual value in months with large positive returns so as to create a "cushion" for those months with lower returns. Such return smoothing behavior yields a more consistent set of returns over time with lower volatility and, therefore, a higher Sharpe ratio, but it also produces serial correlation as a side effect. The more illiquid the portfolio, the more discretion the manager has in marking its value and smoothing returns, creating serial correlation in the process. Cumming and Dai (2010) also show misreporting significantly affects capital allocation, and calculate the wealth transfer effects of misreporting and relate this wealth transfer to differences in hedge fund regulation.

Evidence of possible hedge fund return manipulation is found in some recent studies of misreported returns of hedge fund. Bollen and Pool (2009) find that the number of small gains far exceeds the number of small losses, which is caused at least in part by temporarily overstated returns. Cumming and Dai (2010) further investigate the relation between hedge fund regulations and the misreported returns observed in Bollen and Pool (2009). They find a positive association between wrappers and misreporting, particularly for funds that do not have a lockup provision. They also find some evidence that misreporting is less common among funds in jurisdictions with minimum capitalization requirements and restrictions on the location of key service providers. Agarwal et al. (2009a) find the spike of returns in December for hedge funds with greater incentives and greater opportunities to inflate returns, which suggests that hedge funds manage their returns upwards in an opportunistic fashion in order to earn higher fees. They also provide strong evidence that funds inflate December returns by under-reporting returns earlier in the year, but only weak evidence that funds borrow from January returns in the following year.

Recent studies also link return smoothing to hedge fund failures and frauds. Getmansky et al. (2004b) document the difference in illiquidity risk between active and liquidated funds for 1765 hedge funds in TASS database from 1977 to 2004. They find that graveyard funds exhibit less illiquidity exposure as measured by the serial correlation and the MA(2) smoothed return model of Getmansky et al. (2004a). They also proposed three possible explanations for the difference, including i) live funds may control risks better and, as a result, tend to have smoother returns. ii) funds with smoother returns are more attractive to investors and, therefore, have greater staying power. iii) funds with more illiquidity risk are, on average, compensated for bearing such risk, which in turn implies stronger performance and greater asset-gathering abilities. Bollen and Pool (2008) study the conditional serial correlation in the hedge fund fraud cases recently investigated by the SEC, and find evidence that conditional serial correlation is a leading indicator of fraud.

Goetzmann et al. (2003) point out that the incentive fee contract in hedge funds provides the manager with a call option and theoretically model the value of this option. When a hedge fund receives capital flows at different points in time, the incentive fee contract resembles a portfolio of call options, where each option is related to the capital inflow at a given point in time and has its own strike price (dictated by the NAV at the time of entry and whether the fund has hurdle rate and high-water mark provisions). Following the insights of Goetzmann et al. (2003), Agarwal et al. (2009b) empirically estimate the moneyness and delta of this portfolio of call options. They find that the deltas of the portfolio of incentive contracts are better measures of managerial incentives relative to incentive fee rates.

Managerial incentives and operational risks have been associated with hedge fund performance and misreported returns in some recent studies. Agarwal et al. (2009b) find that hedge funds with greater managerial incentives, proxied by the delta of the option-like incentive fee contracts, higher levels of managerial ownership, and the inclusion of high-water mark provisions in the incentive contracts, are associated with superior performance. Agarwal et al. (2009a) find that funds with greater incentives and greater opportunities to inflate returns exhibit return spikes in December. Cassar and Gerakos (2009) study the mechanisms used to price the funds investment positions and report the funds performance to investors to differentiate between asset illiquidity and misreporting-based explanations. They find that funds using less verifiable pricing sources and funds that provide managers with greater discretion in pricing investment positions are more likely to have returns consistent with intentional smoothing.

2.3 Data

We use the hedge fund data from Lipper TASS database. TASS has monthly net-of-fee returns, assets under management, and other fund characteristics, such as hurdle rates and high-water mark provisions, lockup, notice, and redemption periods, incentive fees, management fees, inception dates, and fund strategies. TASS also classifies hedge funds into 12 strategies: Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity Hedge, Managed Futures, Multi-Strategy, Fund of Funds, and Options Strategy. TASS reports two separate databases, one with "live" funds and another with "graveyard" funds, which keeps track of funds that stop reporting and starts in 1994. Our sample period extends from January 1994 to April 2010. We include both live and graveyard databases and focus on the post-1994 period to mitigate the potential survival-ship bias. As of April 2010, there are 14,177 hedge funds, out of which 5,989 are operational, while 8,188 became defunct during our sample period.

We exclude funds that i) report gross returns, ii) have missing information on management fee or incentive fee,[2] iii) do not report continuously and monthly, and iv) are in the categories of funds of funds, or managed futures, or "other" hedge funds, or have missing strategy information.[3] We delete observations that are backfilled to eliminate backfill bias.[4]

There are additional steps we take to obtain a continuous track of the asset under management (thereafter, AUM) and net asset value (thereafter, NAV) for the algorithm of gross returns and managerial incentives. We delete observations with missing or stale AUM at the beginning or the end of the fund performance history.[5] We also interpolate the missing or stale AUM for up to 3 months, and then keep the longest continuous interval of each fund. We require at least 60 months of returns, and winsorize fund flows at top and bottom 1%.

After these data cleaning steps, we have 1,033 funds in our sample, out of which 539 are live funds and 494 are graveyard funds. The number of funds in each category of live and graveyard databases is given in Table 1.

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[2]If both rates are reported zero, then the fund is also eliminated from the sample.

[3]We exclude funds of funds since it has different fee structure from other fund strategies, see Brown et al. (2004). We exclude managed futures and "other" hedge funds since these categories are not usually considered "typical" hedge funds.

[4]The observation is defined as backfilled if the performance date is before "DateAddedToTass"

[5]Asset Under Management is defined as missing if it is not reported or reported as zero; it is defined as stale if it is equal to its value of the previous month.

AUM[6] and NAV are converted to US dollar, if the original currency is not US dollar. The monthly exchange rates and the three-month London Interbank Offered Rate (LIBOR) of US dollar are downloaded from Bloomberg. The data of trend following factors of Fung and Hsieh (2001) are downloaded from David A. Hsieh's website [7], and the other factors used in Fung and Hsieh (2001) are downloaded from *Yahoo! Finance* [8]. The Credit Suisse/Tremont Hedge Fund Indices used in the conditional return smoothing model are from the Lipper Tass Database.

2.4 Models

In section 2.4.1, we briefly review the unconditional return smoothing model in Getmansky et al. (2004a). In section 2.4.2, we review the conditional return smoothing model in Bollen and Pool (2008).

2.4.1 Unconditional Return Smoothing Model

Getmansky et al. (2004a) examine the econometric properties of reported hedge fund returns by specifying a linear factor model for asset returns and a moving average algorithm that transforms asset returns to reported returns.

We denote by R_t the true return of a hedge funds assets in period t, and assume R_t satisfies the following linear single-factor model:

$$\begin{aligned} & R_t = \mu + \beta\Lambda_t + \varepsilon_t, E[\Lambda_t] = E[\varepsilon_t] = 0, \Lambda_t, \varepsilon_t \sim \text{independent} \\ & Var(R_t) \equiv \sigma^2 \end{aligned} \tag{2.1}$$

[6] "EstimatedAssets" in TASS

[7] http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls

[8] http://finance.yahoo.com

The return of hedge funds assets is known by the funds manager. The reported return of the hedge fund, which is observable by the econometrician, is denoted by R_t^O, and let

$$R_t^O = \theta_0 R_t + \theta_1 R_{t-1} + \cdots + \theta_k R_{t-k} \tag{2.2}$$

$$\theta_j \in [0,1], j = 0, \cdots, k \tag{2.3}$$

and

$$1 = \theta_0 + \theta_1 + \cdots + \theta_k \tag{2.4}$$

which is a weighted average of the funds true returns over the most recent $k+1$ periods, including the current period. The constraint equation (2.4) that the weights sum up to 1 implies that the information driving the fund's performance in period t will eventually be fully reflected in the observed returns, but this process take up to $k+1$ periods from the time the information is generated. From (2.2) to (2.4), the de-meaned observed returns process $X_t = R_t^O - \mu$ is a moving-average process of order k; or an $MA(k)$. Thus, the smoothing profiles can be estimated using maximum-likelihood estimation.

Getmansky et al. (2004a) also introduce a summary statistic for measuring the concentration of weights, called as "smoothing index", which is defined as follows:

$$\xi \equiv \sum_{j=0}^{k} \theta_j^2 \in [0,1] \tag{2.5}$$

Getmansky et al. (2004a) suggest that serial correlation is a proxy for illiquidity and smoothed returns. Lower values of smoothing coefficient θ_0 and smoothing index ξ imply more illiquidity and more smoothed returns.

As stated in Bollen and Pool (2008), the observed returns generated by (2.2) can reflect both conservatism when marking to market and intentionally dampening the observed return process to lower the funds apparent risk. One must be able to distinguish between the two sources of smoothed returns to identify fraudulent reporting. In the unconditional model, however, the two sources of smoothed returns are observationally equivalent. Bollen and Pool (2008) try to the distinguish purposeful managerial smoothing from innocuous causes of serial correlation by modeling the conditional return smoothing based on conditional serial correlation.

2.4.2 Conditional Return Smoothing Model

The smoothing algorithm in equation (2.2) is unconditional in the sense that a fraction θ_0 of the asset return is reported contemporaneously with the remainder reflected in future fund returns, regardless of the value of the asset return. Bollen and Pool (2008) conjecture that competition in the hedge fund industry and the standard compensation scheme for hedge fund managers provide an incentive for a more complex behavior. They argue that managers have an incentive to affect the shape of the reported return distribution in order to make it more attractive to investors. During periods of large positive returns, managers are more likely to fully report fund returns for the fear of lagging behind competitors. During periods of large negative returns, managers may only partially report fund returns to mitigate capital flight.

Bollen and Pool (2008) augment the smoothing algorithm (2.2) to include indicator variables that capture the conditional smoothing:

$$R_t^O = \sum_j^k (\theta_j(1 - I_{t-j}) + \psi_j I_{t-j}) R_{t-j} \quad (2.6)$$

$$I_{t-j} = 1 \text{ if } R_{t-j} > c \text{ for } j = 0, \cdots, k \quad (2.7)$$

$$I_{t-j} = 0 \text{ if } < c \text{ for } j = 0, \cdots, k \quad (2.8)$$

For serial correlation with one lag, the above model can be written as

$$R_t^O = a + (b_1^-(1 - I_{t-1}) + b_1^+ I_{t-1})R_{t-1}^O + \eta_t \tag{2.9}$$

where $I_{t-1} = 1$ if $R_{t-1} > c$ and zero otherwise. If a manager tends to defer reporting poor returns, then the relation between contemporaneous and lagged returns will be larger when the lagged returns are poor, i.e., $b_1^- > b_1^+$.

In later parts of this paper, we will use the conditional serial correlation model following Bollen and Pool (2008):

$$R_t^O = a + b_1^+ R_{t-1}^O + b_1^-(1 - I_{t-1})R_{t-1}^O + \eta_t \tag{2.10}$$

where R_t^O is the observed gross return in month t. $I_{t-1} = 1$ if the fund's systematic return from an optimal factor model at month t-1 is greater than the mean systematic return. Both Credit Suisse/Tremont Hedge Fund indices and the asset-based style (ABS) factors developed by Fung and Hsieh (2004), as well as S&P 500 returns are used as available factors in determining I_{t-1}.[9]

2.5 Empirical Analysis

This section describes our empirical analysis and interprets the results. In section 2.5.1, we present summary statistics for the sample of hedge funds included in our analysis. We implement the models of unconditional return smoothing and conditional smoothing in section 2.4 for each of the funds. Section 2.5.2 reports the estimation of the unconditional return smoothing profiles and the smoothing-adjusted Sharpe ratios, using both gross returns and net returns, and compare the results between gross returns and net returns. Section 2.5.3 examines fund characteristics that

[9] We follow Bollen and Pool (2008), and use stepwise regression to select for a given fund the subset of factors whose contemporaneous and lagged observations maximize the explanatory power (adjusted R^2) of the factor model. We also use feasible generalized least squares with one lag to account for the serial correlation in residuals.

are related to the unconditional serial correlation of hedge fund returns. Section 2.5.4 computes the frequency with which we observe conditional serial correlation. Section 2.5.5 examines fund characteristics that are related to the probability of observing conditional serial correlation. Section 2.5.6 compares dollar incentive fees paid to funds with different degree of return smoothing. Section 2.5.7 examines the return smoothing properties of failed hedge funds in our sample.

2.5.1 Summary Statistics

Table 2.2 contains the basic summary statistics for the 1033 funds in our sample. Both gross returns and net returns are used in the computation of all statistics. There are a lot of variation in mean returns across categories. Emerging markets, Event Driven, Global Macro, and Long/Short Equity Hedge are the strategies with higher mean returns than the other categories. The average gross return is 1.10% monthly, which is higher than the average net returns by 0.32% monthly (i.e. 3.84% annually). For the whole sample, the average standard deviation of monthly gross returns is 4.39%, which is 0.43% higher than that of the net returns. This may be explained by the magnitude of gross returns relative to net returns, as well as the asymmetric incentive contract with high-water mark and hurdle rates. Consistent with the hedge fund literature, funds in our sample are negatively skewed and leptokurtic. Seven of the ten categories have negative skewness, and the average skewness of our sample is -0.24 (using gross returns) and -0.43 (using net returns). All categories have positive excess kurtosis, and the average kurtosis for the sample is 4.94 and 5.42, using gross returns and net returns respectively.

As shown in Table 2.2, hedge funds represent serial correlation across categories. On average, the first serial correlation is 18.92% and 18.81%, estimated using gross returns and net returns respectively. For 8 of the 10 categories, gross returns have higher first order serial correlation than net returns.

By breaking the sample into the live and graveyard fund groups, we find that live funds have higher serial correlation up to first three orders than the graveyard funds, implying that live funds are more illiquid than the graveyard funds. We also find that the difference between the first order serial correlation is only significant for the graveyard fund sample.

566 (503) funds in our sample have significant positive serial correlation in gross (net) returns. This amounts to more than half of our sample. Only 19 (20) funds in our sample have significantly negative serial correlation based on gross (net) returns.

As stated in Getmansky et al. (2004a), serial correlation is a proxy for illiquidity and smoothed returns of hedge fund. These statistics suggest that illiquidity and smoothed returns are important attributes of hedge fund returns.

Table 2.3 reports the statistics of capital flows and fund characteristics. The average monthly fund flow is 2.04% of the assets under management. There are a lot of fluctuations in fund flows, and the standard deviation of monthly fund flow is 22.26%. The funds in our sample have an average (median) age of 125.12 months (116 months). The average fund size is $204.19 million. The lockup period and redemption period are 4.48 months and 3.90 months on average, respectively. There are some variations in lockup period and redemption period across strategies as well. Event driven, Long/Short equity hedge, and Convertible Arbitrage are the categories with the longest lockup and redemption periods. Emerging markets, Fixed Income Arbitrage, and Options Strategy have the shortest lockup period, and Emerging Markets, Global Macro, and Options Strategy have the shortest redemption period.

The percentage rates of management fee and incentive fee, as well as the estimated dollar amount of both fees are reported in Table 2.3. The average rates of management fee and incentive fee are 1.34% and 18.91%, respectively. However, the difference between the estimated dollar amount of management fee and incentive fee is smaller. The average annual management fee per fund is $2,310,270, while the average annual incentive fee per fund is \$3,781,340, which is 1.64 times the amount of the average management fee.

As described previously, we estimate the measures of managerial incentives introduced by Agarwal et al. (2009b), which are the total delta, manager's option delta, and managerial ownership. The *total delta* is the sum of manager's option delta (coming from investors' assets) and the delta from the manager's stake, which is market value of manager's investment in the fund multiplied by 0.01.[10] *Manager's option delta* is defined as the sensitivity of option value to a one percent change in asset value. In the Appendix, we describe the algorithm of computing the monthly delta measures in Feng et al. (2010), which is an extension of the algorithm of delta in Agarwal et al. (2009b), that allows for monthly fees and fund flows, accrual of incentive fees, and inclusion of management fees. As shown in Table 2.3, the mean (median) total delta is \$424,440 (\$373,630). A breakdown of the total delta measure indicates that the mean (median) manager's option delta equals \$232,840 (\$206,360), and the delta from the manager's co-investment in the fund confitures the balance. For our sample, the mean (median) managerial ownership, which is the ratio of our estimate of the manager's co-investment of previously-paid incentive fees to the total assets under management, is 10.17% (7.15%).

2.5.2 Unconditional Return Smoothing

As previously stated, the risk management and return smoothing of hedge fund managers are directly related with the performance of hedge funds gross of all fees. Specifically, the valuation of assets and smoothing of returns both take place before the calculation and deduction of fees. So gross returns provide a clearer picture of hedge fund liquidity and it is also more appropriate for the estimation of return

[10] Agarwal et al. (2009b) assume that managers reinvest all the collected incentive fees in the fund, following the practice of industry practitioners.

smoothing. In this section, we estimate all return smoothing profiles using gross returns, and examine the difference between the results using gross returns and using net returns.

Table 2.4 presents the estimation of smoothing profiles and smoothing index for each fund strategy, using the moving-average model of return smoothing in Getmansky et al. (2004a) reviewed in Section 2.4.1. Getmansky et al. (2004a) suggest using the estimate of smoothing coefficient θ_0 as a proxy of return smoothing and illiquidity. The average value of θ_0 is 0.849, implying that only 84.9% of the true current monthly return would be reported, with the remaining 15.1% distributed over the next two months. Six of the ten categories exhibit smaller average value of θ_0 than the rest: Convertible Arbitrage, Emerging Markets, Event Driven, Fixed Income Arbitrage, Multi-strategy, and Options Strategy. Convertible Arbitrage has the lowest average value of θ_0, which is 0.644, implying that only 64.4% of the current monthly return would be reported, with the remaining 35.6% distributed over the next two months. The smoothing index ξ is also lower for these strategies.

As a robustness check, we also estimate the moving average model under the alternative specification constraint $\sigma = \sigma_{\tilde{NW}}$, where $\sigma_{\tilde{NW}}$ is the Newey-West standard error. While not reported here, the results are similar.

Table 2.4 also compares the estimated return smoothing profiles and smoothing indices of gross returns with those of net returns. For Emerging Markets, Equity Market Neutral, and Long/Short Equity Hedge, the smoothing coefficient θ_0 is significantly lower using gross returns than using net returns. These categories constitute 61.5% of all funds in our sample. For the whole sample, the average estimated θ_0 using gross return is lower than that estimated using net return by 0.6%, and the difference is significant at 1% level. The difference between smoothing profiles θ_1 and θ_2 and the smoothing index ξ of gross returns and of net returns are all significant at the 1% level. As lower smoothing profile θ_0 and smoothing index ξ indicate more illiquidity and smoothed returns, these results imply that net returns tend to underestimate the illiquidity and return smoothing in the unconditional return smoothing model.

We also estimate the risk-adjusted performance measure, i.e. the smoothing-adjusted Sharpe ratio using gross returns, following Lo (2002). Our results confirms the finding of Lo (2002) that annualized Sharpe ratio can be overstated dramatically due to presence of serial correlation in the monthly returns of hedge fund. As shown in Table 2.5, for eight out of ten categories in our sample, the standard Sharpe ratio is significantly higher than the smoothing-adjusted Sharpe ratio. On average, the annualized Sharpe ratio is overstated by 0.23 (0.18), equivalent to 22.5% (21.4%) of the smoothing-adjusted Sharpe ratio of gross (net) returns.

We also compare the Sharpe ratios of gross returns with those of net returns. For all categories, Sharpe ratios of gross returns are significantly higher. This is because the higher level of gross returns dominates the higher volatility of gross returns. As shown in Table 2.2, the average gross returns are higher than average net returns by 0.32% per month (i.e. 3.84% per year), which is equivalent to 41% of the net returns, while the standard deviation of gross returns are only higher than net returns by 0.42, which is equivalent to 11% of the standard deviation of net returns. These results indicate that it is important that we calculate Sharpe ratios separately for gross returns, when we study the risk-adjusted gross-of-fee performance of hedge funds.

In summary, we find that unconditional return smoothing profiles are significantly underestimated using net returns, compared to using gross returns. Sharpe ratios of gross returns are also significantly higher than those of net returns. These results suggest the necessity to use gross returns in the estimation of unconditional return smoothing, as well as the risk-adjusted gross-of-fee performance of hedge funds.

2.5.3 The Determinants of Unconditional Return Smoothing

In this section, we determine whether managerial incentives or any fund characteristics are systematically related to the degree of unconditional serial correlation.

As analyzed in Getmansky et al. (2004a), return smoothing may be resulted from illiquidity as well as intentional smoothing of managers. Previous studies also suggest cross-sectional predictions of the likelihood that a fund manager is manipulating reported returns. Getmansky et al. (2004a) report an adjusted R^2 of 17.7% in a cross-sectional regression of fund smoothing profiles on a number of descriptive indicator variables. They find that, on average, funds that are open to new investors exhibit more smoothing than funds that are not. Bollen and Pool (2008) find that conditional serial correlation is related to the volatility and magnitude of investor cash flows.

We analyze the determinants of serial correlation in subsamples as well as using cross-sectional linear regressions. We estimate the smoothing profiles and smoothing index for subgroups of three categories of variables: managerial incentives, fund flow and performance, and fund characteristics, and examine whether different subsamples exhibit significantly different smoothing profile and smoothing indices. The managerial incentives category variables include total delta, manager's option delta, and managerial ownership as defined in Agarwal et al. (2009b), as well as dollar management fees. The fund flow and performance category variables include the mean and volatility of both capital flows (scaled by lag value of fund asset under management) and the gross returns estimated over the calendar year. The fund characteristics variables include lockup period, redemption period, age, and fund size.

From Table 2.6, we find that the smoothing coefficient θ_0 is significantly lower for funds with higher total delta and funds with higher manager's option delta. The results imply that managerial incentives are associated with more illiquidity and return smoothing. The difference between subgroups of managerial ownership is insignificant. Table 2.6 also reports lower smoothing coefficient θ_0 for funds with higher dollar management fees. As suggested in Agarwal et al. (2009a), funds with higher dollar management fees have greater incentives to manage returns. Our result is consistent with their findings, and implies that these funds have more illiquidity and smoothed returns.

As shown in Table 2.6, the smoothing coefficient θ_0 is significantly lower for funds with high volatility, implying that funds with more volatile returns tend to be less liquid.

Table 2.6 shows that fund with longer redemption periods are significantly higher in unconditional return smoothing. This is consistent with previous literature (See Ding et al. (2009)) in that redemption period, along with other share restrictions, is a measure of the illiquidity of the fund's investment.

From Table 2.6, we also find that large funds exhibit higher unconditional serial correlation than small funds, which implies that large funds are more illiquid or have more return smoothing. As shown in Table 2.7, the measures of managerial incentives, including total delta, manager's option delta, and dollar amount of incentive fee and management fee are all highly correlated with fund size, as the larger the fund is, the higher compensation the fund manager may get for the same returns. Other reasons that may explain the higher level of serial correlation of large funds include the freedom for them to choose among assets, and better skills in managing the illiquid assets.

We find that live funds exhibit more illiquidity and smoothed returns than the graveyard funds. This result is consistent with the finding of Getmansky et al. (2004b), and can be explained by three possible explanations they proposed. First, live funds may control risks better and, as a result, tend to have smoother returns. Second, funds with smoother returns are more attractive to investors and, therefore, have greater staying power. Third, funds with more illiquidity risk are, on average, compensated for bearing such risk, which in turn implies stronger performance and greater asset-gathering abilities. With additional information about the specific investment process of a given fund, it may be possible for an investor to determine which one of these three explanations is most likely to apply on a case-by-case basis.

We do not find significant difference in unconditional serial correlation for high and low groups of mean and volatility of fund flows, fund age, as well as groups of different lockup periods.

The correlation matrix of smoothing profiles and other variables is reported in Table 2.7. The smoothing coefficient θ_0 is negatively correlated with total delta, manager's option delta, managerial ownership, dollar incentive fee, dollar management fee, mean and volatility of capital flows, redemption period, fund age, as well as fund size.

We also use cross-sectional regressions of unconditional serial correlation to see how it is related with managerial incentives and other variables. As reported in Table 2.8, we consider three models. The dependent variable of the first two models is logarithm of the smoothing coefficient θ_0 as the dependent variable, and the dependent variable of the third model is the logarithm of the ξ. In model 1, we include only total delta and control variables such redemption period, age and Live dummy as regressors. In model 2 and 3, we add the mean and volatility of gross returns and of capital flows, and the strategy dummies as the regressors. As θ_0, total delta, the volatility of fund flows and gross returns, and redemption period are all highly skewed, we use the logarithm of these variables to improve their distributional properties.

From Table 2.8, we find that managerial incentive, as measured by total delta, is significant for all three models. It implies that the funds with more managerial incentives tend to have more illiquidity and smoothed returns. Volatility of gross returns is also significantly positive in model 2 and 3, implying that fund with less volatile returns tend to be more illiquid.

As previously discussed, share restrictions such as redemption period are considered as proxies of illiquidity, and have impacts on hedge fund performance and flow-performance relationship (See Aragon (2007) and Ding et al. (2009).). It is not surprising to find significantly negative coefficient of redemption period for all three models of Table 2.8. The result confirms that funds with more illiquidity exhibit more serial correlation.

In Table 2.8, the coefficient of the "Live" dummy is significantly negative for all models, indicating that the funds in the "live" database have more illiquidity and smoothed returns than the funds in the "graveyard" database.

In summary, the subsample analysis and cross-sectional regression of unconditional return smoothing both support that hedge funds with higher managerial incentives tend to exhibit more serial correlation.

2.5.4 Conditional Return Smoothing

To see how many funds exhibit conditional serial correlation, we run the regression following Bollen and Pool (2008):

$$R_t^O = a + b_1^+ R_{t-1}^O + b_1^-(1 - I_{t-1})R_{t-1}^O + \eta_t \tag{2.11}$$

where R_t^O is the observed gross return in month t, and $I_{t-1} = 1$ if the fund's systematic return from an optimal factor model at month t-1 is greater than the mean systematic return. Both Credit Suisse/Tremont Hedge Fund indices and the asset-based style (ABS) factors developed by Fung and Hsieh (2004), as well as S&P 500 returns are used as available factors in determining I_{t-1}. The conditional serial correlation is defined by significant positive b_1^- coefficient.

Table 2.9 lists, for each category, the number of funds and the number of funds that feature b_1^+ and b_1^- coefficients at the two-sided 5% level, when mean strategy return or Fung and Hsieh (2004) seven-factor model are used to infer the indicator variable. As reported in Table 2.2, over half of the funds in sample feature positive serial correlation. In Table 2.9, 28.75% (31.95%) of funds have significant positive b_1^+, for the Credit Suisse/Tremont Indices model and the ABS factor model, respectively. The Convertible arbitrage, Event Driven and Long/Short Equity Hedge categories have the highest number of funds with positive serial correlation. Consistent with the low number of reported fraud cases, the number of funds that feature a significant positive b_1^- are is low, 55 out of 1033 for indices model, and 42 for the ABS factors model, 5.32% and 4.07% in percentage of the whole fund sample, respectively.

We also check the conditional return smoothing frequencies of the subsamples of live and graveyard funds. The percentage of funds featuring conditional return smoothing is higher in live funds than in graveyard funds for both models. However, as we will discuss in later parts, the failed hedge fund sample has the higher frequency of conditional return smoothing than both the live and graveyard subsamples.

2.5.5 The Determinants of Conditional Return Smoothing

In this section, we use the three categories of variables discussed in section 2.5.3 to analyze the determinants of conditional return smoothing.

We first count the number of funds that have conditional serial correlation, detected by significant positive b_1^- coefficients at the two-sided 5% level. Table 2.10 shows that subgroups of funds with greater incentives have more cases of conditional serial correlation, where incentives are proxied by total delta, managerial option delta, managerial ownership, and dollar management fee. The difference between the number of funds for high and low subgroups is significant only for managerial ownership in the Credit Suissee/Tremont indices model. The insignificance of difference between subsamples of other managerial incentive measures may be explained by the limited number of occurrence of conditional return smoothing. However, we do find significant result for total delta in the regression analysis.

Agarwal et al. (2009a) argue that funds with higher volatilities may be able to hide returns management with greater ease. Consistent with this argument, we find funds with higher volatility of gross returns are more likely to exhibit conditional serial correlation, as reported in Table 2.10 for the model using mean strategy return.

From Table 2.10, we also find that funds with shorter redemption period have a significant greater percentage of conditional serial correlation, as funds with shorter redemption period have more incentives to manage returns.

Table 2.11 reports the cross-sectional analysis of conditional serial correlation using logit regressions. The dependent variable equals one if a fund features statistically significant conditional serial correlation, and zero otherwise. We include the same regressors as in the cross-sectional regressions of unconditional return smoothing model.

For both models, we find conditional serial correlation is positively associated with higher managerial incentives (measured by total delta), lower gross returns, and more opportunities to manage returns (measured by volatility of gross returns). We also find funds with redemption period exhibit significant negative relation with conditional serial correlation, in the model using Credit Suissee/Tremont indices for indicator variable estimation. This is consistent with Agarwal et al. (2009a) in that funds with shorter redemption period have more incentives to manage returns.

In summary, we find that conditional return smoothing is associated with greater managerial incentives in both subsample analysis and cross-sectional regressions. Our results imply that funds with greater managerial incentives are more likely to manipulate returns through conditional return smoothing. Further information and investigation may be used in determining the existence of fraud for individual funds.

2.5.6 Are Managers of "Return-Smoothing" Funds Paid More Incentive Fees?

As discussed previously, unconditional serial correlation of returns is considered a proxy for the illiquidity of hedge fund, and along the lines of Aragon (2007), hedge funds with more illiquidity may earn liquidity premium. Hedge fund managers also have the motivation for smoothing return, as they could earn more fees from the smoothed returns. Besides, better risk-adjusted performance from the smoothed returns may help to attract capital flows. Therefore, a natural question would be: do the hedge fund managers really earn more fees from more return smoothing? In this section, we will try to answer this question by calculating the dollar incentive fees for subgroups based on unconditional and conditional return smoothing.

The estimation of dollar incentive fees are reported in Panel A and Panel B of Table 2.12, for subgroups based on unconditional and conditional serial correlation, respectively. The dollar incentive fees are estimated using the algorithm of Feng et al. (2010) as given in the Appendix.

In Panel A, Dedicated Short Bias, Event Driven, Long/Short Equity Hedge and Multi-Strategy have significantly higher dollar incentive fees for the low θ_0 group, which is the group with more unconditional serial correlation. As these categories contain nearly 70% of the funds in our sample, the whole sample also exhibit the same result that funds with higher return smoothing are paid significantly higher incentive fees than other funds. This finding is consistent with Aragon (2007) in that successful funds could earn liquidity premium through investment of illiquid assets.

In Panel B of Table 2.12, we find mixed results for the difference of incentive fees between groups with or without significant conditional serial correlation. Funds featuring conditional serial correlation earn less dollar incentive fee on average for both models. However, the median dollar incentive fee is higher for funds featuring conditional serial correlation in both models.

The contradiction in mean and median results may be explained by the performance distribution of funds featuring conditional serial correlation. In unreporeted results, we find that funds with conditional return smoothing earn a lower return on average, and are more negatively skewed and leptokurtic than the rest of the sample. This implies that there is a lot more tail risk in the returns of funds with conditional return smoothing. As a result, although funds with conditional return smoothing may have a higher chance of earning more returns, they may experience massive capital outflows as well. Therefore, on average, the incentive fees earned by funds exhibiting conditional return smoothing are less than those of other funds. Our results are consistent with the previous studies of liquidity premium, and also caution the risks embedded in the funds manipulating returns for better compensation.

In summary, we find managers of more illiquid funds tend to earn more incentive fees, but funds featuring conditional return smoothing get lower incentive fees on average.

2.5.7 Return Smoothing and Hedge Fund Failures

Major hedge fund databases such as TASS and CISDM include both live and graveyard (dead) hedge funds. However, as hedge funds report to these databases on a voluntary basis, they are free to withdraw from the database for any reason.[11] Liang and Park (2010) find that simple criteria such as performance and change in fund size work better than the stated drop reasons to sort out those discretionarily liquidated funds as well as live funds from the graveyard. The criteria for the "real failure" of hedge funds suggested by Liang and Park (2010) include: i) once listed in

[11] Getmansky et al. (2004b) use the drop reason codes provided by TASS and indicate that liquidation is not the only reason why hedge funds drop out of the live fund database. Other reasons include stop reporting, unable to contact, closed to new investment, merged into another fund, and dormant funds. Feffer and Kundro (2003) argue that hedge fund failure should be distinguished from discretionary fund liquidation, which is much more frequent and is driven by the market expectations of fund managers. They define failed hedge funds as those that have been forced to cease investment operations for reasons outside managements control.

a database but stopped reporting, ii) negative average rate of return for the last 6 months, and iii) decreased AUM for the last 12 months. In this section, we examine the unconditional and conditional return smoothing for the failed hedge funds, which is defined by the criteria used in Liang and Park (2010).

The results of unconditional and conditional serial correlation of the subsample of "real failure" hedge funds as defined above are reported in Table 2.13 and Table 2.14, respectively.

Compared with Table 2.4, eight of the ten categories in Table 2.13 have lower smoothing coefficient θ_0, with the exceptions being Global Macro and Options strategy, which both have only a few failed funds in the sample. The result implies that the failed hedge funds tend to exhibit more illiquidity and smoothed returns. The comparison between the failure sample with other funds also shows that the smoothing coefficient θ_0, as well as the smoothing index ξ are significantly lower for the failed funds, which implies more illiquidity and return smoothing in the failed hedge funds.

As shown in Table 2.14, the percentage of funds featuring significant conditional serial correlation detected using Credit Suissee/Tremont indices and the ABS factor model are 6.90% and 85.91%, respectively. These numbers are both higher than the corresponding results, 5.32% and 4.07%, respectively for the whole sample, and 4.25% and 3.64%, respectively for the graveyard sample. It implies that the failed hedge funds tend to have more conditional return smoothing.

These results are interesting. In Table 2.4 and Table 2.9, we find that graveyard funds tend to have less illiquidity and return smoothing in general. However, the subgroup of "real failure" hedge funds exhibit more illiquidity and return smoothing under the measures of both conditional and unconditional serial correlation. This may be explained the other side of the liquidity premium story of Aragon (2007). While successful funds could manage the illiquidity assets and earn liquidity premium on them, failing to do so may result in hedge fund failures. The higher percentage of conditional return smoothing in these funds also suggest a careful examination of misreport or misrepresentation of fund returns on these failed funds.

2.6 Conclusion

Recent literature documents that hedge funds have high serial correlation in their returns. It also suggests that the conditional serial correlation could be used as a first screen for manipulation of fund returns and hedge fund fraud. We use gross returns and managerial incentive measures, estimated from a comprehensive algorithm, to study the return smoothing properties of both regular and failed hedge funds, and document several interesting findings.

First, we find levels of illiquidity and return smoothing are significantly underestimated using net returns, especially for the graveyard funds. Therefore, using gross returns to estimate return smoothing is both more appropriate and more accurate. We also estimate both the standard and the smoothing-adjusted Sharpe ratios using gross returns, and find that they are significantly higher than those using net returns. This suggests the necessity of a separate calculation of Sharpe ratios for the gross-of-fee risk-adjusted performance.

Second, we find that funds with greater managerial incentives tend to have more illiquidity and return smoothing. Higher managerial incentives are also related to conditional return smoothing, which is a leading indicator of fraud. Furthermore, we find managers of more illiquid funds tend to earn more incentive fees. However, funds featuring conditional return smoothing on average earn less fees.

Finally, we study the return smoothing properties of "real failure" hedge funds, where the failure of hedge funds is defined not only by their status as graveyard funds, but also using performance measures to distinguish them from liquidated funds in the graveyard funds. We find that graveyard funds tend to have less illiquidity and return smoothing in general. However, the subgroup of "real failure" hedge funds exhibit more illiquidity and return smoothing under the measures of both conditional and unconditional serial correlation. While successful funds could manage the illiquidity assets and earn liquidity premium on them, failing to do so may result in hedge fund failures. The higher percentage of conditional return smoothing in these funds also suggest a careful examination of misreport or misrepresentation of fund returns on these failed funds.

Overall, our findings suggest that managers with greater incentives tend to exhibit more illiquidity and smoothed returns. They may earn more incentive fees from liquidity premiums and attract more investment with better risk-adjusted performance, but may not necessarily earn more fees by manipulating returns. The significant difference between the return smoothing properties of failed funds and non-failed funds also suggests the possibility of using return smoothing models to forecast hedge fund failures.

Table 2.1. Number of Funds in the TASS Hedge Fund Live and Graveyard Databases

In this table we report the number of hedge funds in TASS database having at least five years of return history in our sample, from January 1994 to April 2010.

Category	Number of funds		
	Combined	Live	Graveyard
Convertible Arbitrage (CA)	52	15	37
Dedicated Short Bias (DSB)	9	1	8
Emerging Markets (EM)	109	68	41
Equity Market Neutral (EMN)	60	26	34
Event Driven (ED)	145	68	77
Fixed Income Arbitrage (FIA)	55	22	33
Global Macro (GM)	54	29	25
Long/Short Equity Hedge (LSEH)	466	261	205
Multi-Strategy (MS)	78	45	33
Options Strategy (OS)	5	4	1
All	1033	539	494

Table 2.2. Summary Statistics: Gross Return vs Net Return

Listed are summary statistics of both gross and net returns of hedge funds in TASS combined database with at least 60 months of return history from January 1994 to April 2010. Both gross returns (GR) and net returns (NR) are used in the computation of all statistics. The *mean*, *median*, and standard deviation (*StdDev*) of monthly returns are reported in percentage. *Skew* measures skewness, and *Kurt* measures excess kurtosis, i.e. the fourth moment around the mean divided by the square of the variance of the probability distribution minus 3. The difference of statistics between gross returns and net returns are reported, with ***, ** and * denoting significance of t test at the 1%, 5%, and 10% levels. We also reported the first three order serial correlations (ρ_1, ρ_2, and ρ_3), and number of funds with significant positive (*#Pos*) and significant negative (*#Neg*) first order serial correlation at 5% level.

Panel A: All Funds, Including Both Live and Graveyard Funds

Category	N		Mean (%)	Median (%)	StdDev (%)	Skew	Kurt	ρ_1 (%)	ρ_2 (%)	ρ_3 (%)	# Pos	# Neg
		GR	0.694	0.900	2.872	-0.980	8.748	39.900	16.942	9.966	47	0
CA	52	NR	0.451	0.682	2.657	-1.188	9.632	39.478	15.857	9.201	47	0
		diff	0.243 ***	0.218 ***	0.214 ***	0.208 ***	-0.885 ***	0.422 **	1.085 ***	0.765 ***		
		GR	0.481	0.079	5.383	0.239	0.762	14.267	1.317	1.848	4	0
DSB	9	NR	0.217	-0.019	4.893	0.123	0.547	13.865	2.250	0.818	4	0
		diff	0.264 ***	0.098 **	0.491 ***	0.116 ***	0.215 *	0.401 *	-0.932 **	1.030		
		GR	1.474	1.571	6.812	-0.532	5.761	22.661	12.887	5.660	70	0
EM	109	NR	1.061	1.265	6.305	-0.756	6.599	23.077	13.079	5.660	71	0
		diff	0.413 ***	0.306 ***	0.508 ***	0.224 ***	-0.838 ***	-0.416 **	-0.193	-0.001		
		GR	0.820	0.821	3.133	-0.589	9.788	13.743	6.955	4.382	26	2
EMN	60	NR	0.556	0.611	2.825	-0.740	10.001	12.901	6.797	4.087	24	3
		diff	0.263 ***	0.210 ***	0.308 ***	0.150 ***	-0.213 ***	0.842 **	0.158	0.295		
		GR	1.023	1.076	2.677	-0.473	5.232	27.258	13.335	9.836	109	1
ED	145	NR	0.721	0.812	2.381	-0.679	6.103	27.130	13.007	9.413	106	1
		diff	0.302 ***	0.264 ***	0.296 ***	0.206 ***	-0.871 ***	0.128	0.328 **	0.423 ***		
		GR	0.873	0.981	3.409	-1.667	14.991	23.137	11.492	10.050	34	4
FIA	55	NR	0.583	0.730	3.148	-1.893	16.459	22.995	11.181	9.899	35	4
		diff	0.290 ***	0.251 ***	0.261 ***	0.226 ***	-1.468 ***	0.142	0.311	0.151		
		GR	1.431	1.135	4.719	0.440	3.319	7.055	0.310	2.344	14	2
GM	54	NR	1.044	0.882	4.142	0.309	3.299	7.177	0.178	2.092	15	3
		diff	0.387 ***	0.253 ***	0.578 ***	0.131 ***	0.020	-0.122	0.132	0.253 *		
		GR	1.131	1.064	4.869	0.106	2.819	14.112	4.480	3.718	208	10
LSEH	466	NR	0.811	0.838	4.401	-0.055	3.039	14.014	4.018	3.494	202	9
		diff	0.320 ***	0.227 ***	0.468 ***	0.161 ***	-0.220 ***	0.098	0.462 ***	0.224 ***		
		GR	1.048	1.048	3.721	-0.310	4.031	22.474	7.516	7.591	51	0
MS	78	NR	0.723	0.793	3.349	-0.541	4.580	22.290	7.554	7.343	49	0
		diff	0.325 ***	0.255 ***	0.371 ***	0.231 ***	-0.549 ***	0.184	-0.038	0.248		
		GR	0.890	0.822	3.108	0.689	6.440	22.833	3.104	-1.771	3	0
OS	5	NR	0.590	0.605	2.696	0.514	5.644	22.105	1.209	-1.958	3	0
		diff	0.299 ***	0.217 ***	0.411 ***	0.175 ***	0.796 ***	0.727	1.895 **	0.186		
		GR	1.172	1.208	4.454	-0.276	4.043	20.341	8.462	6.579	318	7
Live	539	NR	0.840	0.948	4.045	-0.456	4.581	20.413	8.149	6.336	315	8
		Diff	0.332 ***	0.259 ***	0.409 ***	0.180 ***	-0.538 ***	-0.071	0.313 ***	0.243 ***		
		GR	1.022	0.952	4.317	-0.205	5.912	17.375	6.935	4.636	248	12
Graveyard	494	NR	0.713	0.727	3.899	-0.390	6.329	17.066	6.608	4.345	241	12
		Diff	0.310 ***	0.225 ***	0.418 ***	0.185 ***	-0.417 ***	0.309 ***	0.327 ***	0.290 ***		
		GR	1.101	1.085	4.389	-0.242	4.937	18.923	7.732	5.650	566	19
All	1033	NR	0.779	0.843	3.975	-0.425	5.417	18.812	7.412	5.384	556	20
		Diff	0.322 ***	0.243 ***	0.413 ***	0.183 ***	-0.480 ***	0.110 **	0.320 ***	0.266 ***		

Panel B: Graveyard Funds, Including Liquidated and Failed Funds

Category	N		Mean (%)	Median (%)	StdDev (%)	Skew	Kurt	ρ_1 (%)	ρ_2 (%)	ρ_3 (%)	# Pos	# Neg
		GR	0.617	0.834	2.876	-0.878	9.147	36.691	16.200	10.452	33	0
CA	37	NR	0.387	0.629	2.661	-1.062	9.873	36.334	15.564	10.193	33	0
		diff	0.230 ***	0.205 ***	0.215 ***	0.184 ***	-0.726 ***	0.357	0.636 ***	0.259		
		GR	0.471	0.000	5.601	0.244	0.894	14.748	1.983	1.291	4	0
DSB	8	NR	0.209	-0.094	5.107	0.137	0.664	14.380	2.925	-0.255	4	0
		diff	0.263 ***	0.094 **	0.494 ***	0.107 ***	0.230 *	0.368	-0.941 *	1.546 **		
		GR	1.079	1.225	7.683	-0.627	4.911	15.142	4.244	-2.853	19	0
EM	41	NR	0.739	0.979	7.189	-0.835	5.792	15.370	4.432	-2.849	19	0
		diff	0.340 ***	0.246 ***	0.494 ***	0.208 ***	-0.882 ***	-0.228	-0.188	-0.004		
		GR	0.762	0.780	3.327	-0.903	14.912	15.105	8.510	6.789	16	2
EMN	34	NR	0.513	0.585	3.036	-1.034	15.035	14.433	8.595	6.820	15	2
		diff	0.249 ***	0.195 ***	0.291 ***	0.131 ***	-0.123	0.672 *	-0.085	-0.031		
		GR	1.057	1.034	2.366	-0.262	4.436	24.328	11.714	7.458	57	1
ED	77	NR	0.749	0.773	2.061	-0.452	5.365	24.035	11.486	7.000	55	1
		diff	0.307 ***	0.261 ***	0.305 ***	0.191 ***	-0.929 ***	0.293	0.229	0.458 ***		
		GR	0.869	1.024	3.052	-1.934	17.557	21.486	10.840	10.447	21	2
FIA	33	NR	0.576	0.755	2.795	-2.165	19.155	21.017	10.397	10.332	21	2
		diff	0.293 ***	0.269 ***	0.257 ***	0.231 ***	-1.598 ***	0.469 *	0.443	0.115		
		GR	1.315	1.063	4.699	0.610	5.365	6.474	-1.126	3.586	7	2
GM	25	NR	0.940	0.808	4.130	0.448	5.310	6.511	-1.350	3.324	8	2
		diff	0.375 ***	0.255 ***	0.569 ***	0.161 ***	0.054	-0.037	0.224	0.262		
		GR	1.133	0.932	5.073	0.288	3.086	12.029	4.575	3.075	70	5
LSEH	205	NR	0.810	0.728	4.559	0.113	3.117	11.681	3.979	2.694	65	5
		diff	0.323 ***	0.203 ***	0.514 ***	0.176 ***	-0.031	0.349 ***	0.597 ***	0.382 ***		
		GR	0.973	0.944	3.316	-0.241	4.825	22.515	5.780	4.287	20	0
MS	33	NR	0.650	0.681	2.943	-0.480	5.277	22.085	5.879	4.357	20	0
		diff	0.324 ***	0.263 ***	0.372 ***	0.239 ***	-0.452	0.430	-0.098	-0.071		
		GR	0.888	0.442	3.403	3.262	19.695	20.173	-13.106	-1.545	1	0
OS	1	NR	0.571	0.250	2.895	2.713	16.111	20.020	-12.354	-2.679	1	0
		diff	0.317	0.192	0.508	0.549	3.584	0.153	-0.753	1.134		
		GR	0.899	0.837	4.024	0.031	3.604	15.056	6.606	4.580	75	5
Liquidated	178	NR	0.607	0.632	3.616	-0.155	3.835	14.836	6.150	4.120	75	5
		Diff	0.292 ***	0.205 ***	0.408 ***	0.186 ***	-0.231 ***	0.220	0.455 ***	0.460 ***		
		GR	0.837	0.829	4.652	-0.578	7.783	19.894	9.208	5.460	116	4
Failed Funds	203	NR	0.536	0.621	4.236	-0.803	8.268	19.863	8.837	5.127	116	4
		Diff	0.301 ***	0.208 ***	0.416 ***	0.225 ***	-0.485 ***	0.030	0.371 ***	0.333 ***		
		GR	1.022	0.952	4.317	-0.205	5.912	17.375	6.935	4.636	248	12
Graveyard	494	NR	0.713	0.727	3.899	-0.390	6.329	17.066	6.608	4.345	241	12
		Diff	0.310 ***	0.225 ***	0.418 ***	0.185 ***	-0.417 ***	0.309 ***	0.327 ***	0.290 ***		

Table 2.3. Statistics of Fund Characteristics, Flow, and Managerial Incentives

This table reports summary statistics of fund characteristics, capital flows and managerial incentives for funds in our sample from January 1994 to April 2010. Panel A show statistics for all funds, and panel B show statistics for each strategy. *Total Delta* is the total expected dollar change in the manager's wealth for a 1% change in NAV. *Mgr's Opt Delta* is the delta from incentive contracts. *Mgr Ownership* is the percentage of manager's investment in the fund to the total asset under management. *Flow* is the monthly capital flow scaled by the previous end-of-month AUM, reported in percentage. *Volatility* is standard deviation of monthly gross returns estimated over the calendar year. *$MF* and *$IF* are the annual dollar amount of management fee and the annual dollar amount of incentive fees respectively, reported in million US dollars. *Lockup Period* is lockup period in years based on funds that have nonzero lockup period. *Redemp Period* is the sum of RedemptionNoticePeriod and RedemptionFrequency, reported in years. Age is age of funds in years. AUM is the monthly average of fund asset under management, given as millions of US dollars. *MF (%)* and *IF (%)* are the percentage rates of management fee and incentive fee respectively. In Panel B, all variables are reported in mean.

Panel A: All Funds

Variable	N	Mean	StdDev	Min	Median	Max
Age (yr)	1033	10.43	3.89	5.08	9.67	32.42
AUM ($MM)	1033	204.19	414.56	0.37	75.61	5981.84
MF (%)	1033	1.34	0.47	0.00	1.25	4.00
IF (%)	1033	18.91	4.40	0.00	20.00	50.00
Lockup Period (yr)	352	1.10	0.71	0.08	1.00	7.50
Redemp Period (yr)	1033	0.33	0.26	0.00	0.33	1.50
Flow (%)	1033	2.04	22.26	-35.91	0.08	163.49
Volatility (%)	1033	3.77	2.40	0.05	3.31	15.62
$MF ($MM)	1033	2.31	1.60	0.37	2.07	4.79
$IF ($MM)	1033	3.78	4.12	0.13	2.66	11.43
Total Delta ($MM)	1033	0.42	0.28	0.11	0.37	0.88
Mgr's Opt Delta ($MM)	1033	0.23	0.17	0.05	0.20	0.50
Mgr Ownership (%)	1033	10.17	9.91	0.03	7.15	34.73

Panel B: By Strategy

Category	N	Age (yr)	AUM ($MM)	MF (%)	IF (%)	Lockup Period (yr)	Redemp Period (yr)	Flow (%)	Volatility (%)	$MF ($MM)	$IF ($MM)	Total Delta ($MM)	Mgr's Opt Delta ($MM)	Mgr Owner-ship (%)
CA	52	10.23	132.50	1.20	18.46	1.03	0.30	1.07	2.23	1.39	1.76	0.26	0.18	8.07
DSB	9	9.23	29.26	1.28	16.39	0.75	0.24	2.76	4.96	0.36	0.30	0.03	0.02	7.95
EM	109	10.10	162.53	1.57	17.68	1.01	0.27	0.61	5.83	2.17	3.53	0.37	0.16	13.40
EMN	60	10.06	155.18	1.38	18.33	0.85	0.22	2.89	2.41	1.84	1.39	0.23	0.16	7.85
ED	145	11.37	301.97	1.32	19.36	1.26	0.52	1.68	2.20	3.68	5.75	0.63	0.40	7.58
FIA	55	9.88	265.48	1.42	20.02	0.73	0.31	3.19	2.53	3.19	4.00	0.58	0.34	9.60
GM	54	9.66	382.33	1.55	18.69	1.25	0.21	5.81	4.28	4.20	8.98	0.93	0.41	9.88
LSEH	466	10.40	156.54	1.22	19.03	1.07	0.33	1.07	4.29	1.51	3.17	0.34	0.17	10.67
MS	78	10.83	312.42	1.57	19.36	1.40	0.29	7.08	3.21	4.12	4.11	0.51	0.30	11.46
OS	5	9.65	79.41	1.60	20.00	0.42	0.20	0.50	2.51	1.11	1.39	0.17	0.10	10.98

Table 2.4. Unconditional Smoothing Profile and Smoothing Index

This table reports the means and standard deviations of the maximum likelihood estimates of the unconditional smoothing profile and smoothing index introduced in Getmansky et al. (2004b), for hedge funds in the TASS combined database with at least five years of returns history during the period from January 1994 to April 2010. The smoothing profile is estimated using MA(2) smoothing process $R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}$, and the smoothing index is defined as $\xi = \theta_0^2 + \theta_1^2 + \theta_2^2$. MA(2) is estimated under the identification constraint $\theta_0 + \theta_1 + \theta_2 = 1$. All estimates are calculated using gross return (GR) and net return (NR) respectively, and the difference between the estimates of smoothing profile and smoothing index using GR and NR (diff) are reported, with ***, ** and * denoting significance at the 1%, 5%, and 10% levels.

Category		N	θ_0		θ_1		θ_2		ξ	
			Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Convertible Arbitrage	GR	52	0.644	0.191	0.249	0.180	0.107	0.114	0.568	0.361
	NR	52	0.648	0.208	0.248	0.198	0.104	0.123	0.588	0.432
	diff		-0.005		0.001		0.003		-0.020	*
Dedicated Short Bias	GR	9	0.869	0.068	0.143	0.071	-0.012	0.081	0.790	0.102
	NR	9	0.864	0.063	0.135	0.068	0.001	0.075	0.777	0.095
	diff		0.005		0.007	**	-0.013	**	0.013	
Emerging Markets	GR	109	0.773	0.146	0.149	0.103	0.079	0.088	0.665	0.244
	NR	109	0.770	0.153	0.151	0.106	0.079	0.092	0.665	0.264
	diff		0.002	*	-0.002	**	0.000		0.000	
Equity Market Neutral	GR	58	0.913	0.306	0.056	0.224	0.032	0.189	1.014	0.899
	NR	58	0.927	0.320	0.045	0.241	0.028	0.189	1.055	0.990
	diff		-0.014	***	0.010	**	0.004		-0.042	*
Event Driven	GR	145	0.754	0.150	0.185	0.113	0.061	0.104	0.653	0.231
	NR	144	0.755	0.156	0.185	0.117	0.060	0.108	0.657	0.239
	diff		-0.001		0.000		0.001		-0.005	**
Fixed Income Arbitrage	GR	54	0.827	0.335	0.124	0.291	0.049	0.163	0.921	0.992
	NR	53	0.843	0.376	0.115	0.327	0.042	0.169	0.996	1.324
	diff		-0.015		0.008		0.007		-0.075	
Global Macro	GR	53	0.973	0.217	0.056	0.151	-0.029	0.138	1.039	0.538
	NR	53	0.975	0.225	0.055	0.155	-0.031	0.140	1.048	0.565
	diff		-0.002		0.001		0.001		-0.009	
Long/Short Equity Hedge	GR	462	0.893	0.277	0.100	0.162	0.007	0.180	0.943	1.181
	NR	462	0.901	0.304	0.098	0.175	0.001	0.195	0.982	1.468
	diff		-0.008	***	0.002		0.006	***	-0.040	***
Multi-Strategy	GR	76	0.804	0.168	0.166	0.101	0.030	0.123	0.728	0.290
	NR	78	0.817	0.202	0.160	0.107	0.023	0.146	0.766	0.424
	diff		-0.012		0.006	*	0.007		-0.038	
Options Strategy	GR	5	0.785	0.118	0.174	0.094	0.041	0.084	0.672	0.143
	NR	5	0.800	0.130	0.176	0.100	0.024	0.077	0.698	0.154
	diff		-0.015		-0.003		0.018	*	-0.026	*

Table 2.5. Smoothing-Adjusted Sharpe Ratios

This table compares the mean and standard deviation of the standard Sharpe ratio with the smoothing-adjusted annualized Sharpe ratios in Lo (2002), for hedge funds in the TASS combined database with at least five years of returns history during the period from January 1994 to April 2010. All estimates are calculated using gross return (GR) and net return (NR) respectively. The difference between two Sharpe ratio measures is reported as $SR - SR^*$, with ***, ** and * denoting significance at the 1%, 5%, and 10% levels

Category	N		SR		SR^*		$SR - SR^*$	
			Mean	StdDev	Mean	StdDev		
		GR	1.67	2.94	1.02	1.39	0.65	***
Convertible Arbitrage	52	NR	1.41	2.94	0.85	1.34	0.56	**
		diff	0.26	***	0.18	***		
		GR	0.35	0.37	0.31	0.33	0.04	*
Dedicated Short Bias	9	NR	0.18	0.33	0.17	0.29	0.01	
		diff	0.16	***	0.13	***		
		GR	0.94	0.73	0.76	0.66	0.17	***
Emerging Markets	109	NR	0.76	0.69	0.63	0.64	0.13	***
		diff	0.18	***	0.14	***		
		GR	1.45	1.52	1.20	0.80	0.25	*
Equity Market Neutral	60	NR	1.17	1.29	0.99	0.73	0.18	
		diff	0.28	***	0.21	***		
		GR	1.76	1.18	1.31	0.89	0.46	***
Event Driven	145	NR	1.47	1.11	1.10	0.83	0.37	***
		diff	0.29	***	0.20	***		
		GR	2.90	8.63	1.96	5.35	0.93	*
Fixed Income Arbitrage	55	NR	2.49	7.96	1.65	4.75	0.83	
		diff	0.41	***	0.31	***		
		GR	1.08	0.47	1.08	0.55	0.00	
Global Macro	54	NR	0.90	0.46	0.91	0.53	-0.01	
		diff	0.18	***	0.17	***		
		GR	0.93	0.50	0.86	0.49	0.07	***
Long/Short Equity Hedge	466	NR	0.75	0.47	0.71	0.46	0.04	***
		diff	0.18	***	0.15	***		
		GR	1.27	0.79	1.02	0.55	0.25	***
Multi-Strategy	78	NR	1.01	0.74	0.82	0.51	0.20	***
		diff	0.25	***	0.20	***		
		GR	1.14	0.62	1.15	0.93	-0.02	
Options Strategy	5	NR	0.87	0.51	0.92	0.78	-0.04	
		diff	0.26	***	0.24	**		

Table 2.6. Unconditional Return Smoothing for Subsamples

This table reports the mean and standard deviation of smoothing profile and smoothing index estimated using MA(2) model in Getmansky et al. (2004b) for subsamples of hedge funds. Other variables are defined in Table 2.3, and the high (low) groups consist of funds whose characteristic is greater than or equal to (less than) the median value in the same category. The differences of average return smoothing profiles and smoothing indices for high and low subsamples are reported, with ***, ** and * denoting significance at the 1%, 5%, and 10% levels.

Subsample	θ_0			θ_1			θ_2			ξ		
	Mean	diff		Mean	diff		Mean	diff		Mean	diff	
High Total Delta	0.81			0.15			0.04			0.79		
Low Total Delta	0.87	-0.07	***	0.11	0.04	***	0.02	0.03	***	0.89	-0.11	*
High Mgr Opt Delta	0.81			0.15			0.04			0.80		
Low Mgr Opt Delta	0.87	-0.06	***	0.11	0.04	***	0.02	0.02	**	0.88	-0.08	
High Mgr Ownership	0.84			0.13			0.03			0.84		
Low Mgr Ownership	0.84	0.00		0.12	0.00		0.03	0.00		0.85	-0.01	
High $ Management Fee	0.82			0.15			0.04			0.80		
Low $ Management Fee	0.87	-0.05	***	0.11	0.04	***	0.02	0.02		0.89	-0.09	
High Volatility	0.89			0.11			0.00			0.93		
Low Volatility	0.80	0.09	***	0.14	-0.03	***	0.06	-0.06	***	0.75	0.18	***
High Flow (%)	0.84			0.13			0.03			0.85		
Low Flow (%)	0.85	-0.01		0.13	0.00		0.03	0.01		0.83	0.03	*
High Flow Volatility	0.85			0.12			0.03			0.90		
Low Flow Volatility	0.83	0.02		0.13	-0.01		0.04	-0.01		0.79	0.11	
Short Lockup	0.84			0.13			0.04			0.80		
Long Lockup	0.85	-0.02		0.13	0.00		0.02	0.02		0.93	-0.13	*
Short Redemption Period	0.87			0.11			0.02			0.90		
Long Redemption Period	0.81	0.06	***	0.15	-0.04	***	0.04	-0.01		0.78	0.11	**
Young	0.85			0.12			0.03			0.89		
Senior	0.83	0.02		0.13	-0.01		0.03	-0.01		0.80	0.09	
Large Size	0.81			0.15			0.04			0.79		
Small Size	0.87	-0.06	***	0.11	0.04	***	0.02	0.02	*	0.89	-0.10	*
Graveyard	0.86			0.11			0.03			0.89		
Live	0.83	0.04	**	0.14	-0.03	**	0.04	-0.01		0.80	0.09	*

Table 2.7. Correlation Matrix of Smoothing Profile, Smoothing Index and Other Variables

This table reports the correlation matrix of the estimated smoothing profile (θ_0), smoothing index (ξ) of the unconditional return smoothing model of Getmansky et al. (2004a) and other variables, including total delta, manager's option delta (*Mgr's Opt Delta*), managerial ownership (*Mgr Ownership*), annual dollar incentive fee (*$IF*), annual dollar management fee (*$MF*), mean ($\mu_{flow}$) and volatility ($\sigma_{flow}$) of monthly flow as a percentage of AUM, the mean (μ_{GR}), fractional rank (*GR_rank*), and volatility (σ_{GR}) of gross returns, lockup period (*Lockup*), redemption period (*Redemp*), age, and fund size. All numbers are reported in percentage.

	θ_0	ξ	Total Delta	Mgr's Opt Delta	Mgr Own-ership	$IF	$MF	μ_{GR}	σ_{GR}	μ_{flow}	σ_{flow}	Lockup	Redemp	Age	Size
θ_0	100.00														
ξ	87.67	100.00													
Total Delta	-7.31	-4.90	100.00												
Mgr's Opt Delta	-9.01	-5.33	91.55	100.00											
Mgr Ownership	-0.25	-1.01	5.75	-7.23	100.00										
$IF	-6.30	-4.69	95.51	87.60	2.60	100.00									
$MF	-7.31	-4.73	83.14	89.02	-6.98	77.61	100.00								
μ_{GR}	6.46	4.26	16.75	6.12	24.35	24.37	7.69	100.00							
σ_{GR}	17.65	10.29	-4.48	-15.19	27.63	1.63	-13.18	42.00	100.00						
μ_{flow}	-0.68	-0.66	0.22	1.26	-5.87	0.08	2.32	3.08	-2.46	100.00					
σ_{flow}	-0.10	-0.53	-0.88	-0.53	-1.56	-1.60	0.75	0.89	-1.18	99.35	100.00				
Lockup	0.79	2.66	3.14	5.31	-12.40	3.98	3.57	2.35	1.59	-2.62	-3.49	100.00			
Redemp	-11.04	-7.39	13.66	17.20	-14.35	15.94	10.18	5.34	-4.93	-5.69	-6.47	25.16	100.00		
Age	-5.69	-6.56	16.77	15.70	11.72	14.36	13.17	-2.09	0.62	-7.89	-6.08	-2.15	23.88	100.00	
Size	-7.98	-5.03	94.32	97.69	-4.58	91.02	91.04	9.04	-10.04	1.05	-0.52	4.39	14.66	16.58	100.00

Table 2.8. Unconditional Smoothing: Cross-Sectional Regression Analysis

This table reports the results of cross-sectional regression with smoothing profile θ_0, or smoothing index ξ as the dependent variable. The smoothing profile and smoothing index are estimated using the MA(2) model of returns as in Getmansky et al. (2004b). Independent variables are log(delta), the natural logarithm of the fund's total delta, μ_{GR}, the average gross returns of each fund, $\log(\sigma_{GR})$, the natural logarithm of the volatility of gross returns estimated over the calendar year, μ_{flow}, the monthly mean investor cash flow as a percentage of fund assets, $\log(\sigma_{flow})$, the natural logarithm of the volatility of investor cash flows as a percentage of fund assets, log(Redemp), the natural logarithm of redemption period in month, Age, the age of funds in months, and Live, an indicator variable that equals one if the fund is live as of April 2010. Dummy variables of broad strategies are defined following Agarwal et al. (2009b). ***, ** and * denote significance at the 1%, 5%, and 10% levels.

	Model 1			Model 2			Model 3		
				Dependent Variable					
	$\log(\theta_0)$			$\log(\theta_0)$			$\log(\xi)$		
	Coeff		p-value	Coeff		p-value	Coeff		p-value
Intercept	0.0005		0.9935	0.2522	***	0.0008	0.4211	***	0.0015
log(delta)	-0.0181	***	0.0003	-0.0143	***	0.0059	-0.0236	**	0.0100
μ_{GR}				1.0564		0.4379	1.4391		0.5503
$\log(\sigma_{GR})$				0.0745	***	0.0000	0.1152	***	0.0000
μ_{flow}				-0.0196		0.6884	-0.0320		0.7106
$\log(\sigma_{flow})$				0.0089		0.4086	0.0080		0.6731
log(Redemp)	-0.0471	***	8E-06	-0.0458	***	0.0000	-0.0692	***	0.0002
Age	0.0002		0.3129	0.0002		0.3096	0.0001		0.8030
Live	-0.0387	**	0.0121	-0.0439	***	0.0039	-0.0833	***	0.0020
Strategy Dummies	No			Yes			Yes		
R^2	0.1056			0.1425			0.1107		
Adj-R^2	0.0992			0.1328			0.1006		

Table 2.9. Frequency of Conditional Serial Correlation

This table reports the number and percentage of funds with significant positive and significant negative coefficients evaluated at the two-sided 5% level for each category of hedge funds. The regression model for conditional serial correlation follows Bollen and Pool (2008), i.e. $R_t^O = a + b_1^+ R_{t-1}^O + b_1^-(1 - I_{t-1})R_{t-1}^O + \eta_t$, where R_t^O is the observed gross return in month t and I_{t-1} equals one if the fund's systematic return from an optimal factor model at month t-1 is greater than the mean systematic return. Listed are results when Credit Suisse/Tremont Hedge Fund indices, as well as the asset-based style (ABS) factors developed by Fung and Hsieh (2004) are used as available factors in determining I_{t-1}.

Category		Credit Suisse/Tremont Indices				ABS Factors			
	N	Pos	Neg	Pos	Neg	Pos	Neg	Pos	Neg
Convertible Arbitrage	52	38	0	4	5	39	1	5	3
Dedicated Short Bias	9	0	0	1	0	1	0	0	0
Emerging Markets	109	27	0	4	2	37	1	3	2
Equity Market Neutral	60	16	0	3	10	15	2	3	10
Event Driven	145	75	1	4	9	83	1	4	17
Fixed Income Arbitrage	55	21	3	4	7	22	2	2	8
Global Macro	54	4	1	3	2	3	1	3	2
Long/Short Equity Hedge	466	90	2	24	19	97	5	19	24
Multi-Strategy	78	25	0	7	3	32	0	3	4
Options Strategy	5	1	0	1	0	1	0	0	0
Live	539	142	2	34	23	171	6	24	31
(% Rejections)		26.35%	0.37%	6.31%	4.27%	31.73%	1.11%	4.45%	5.75%
Graveyard	494	155	5	21	34	159	7	18	39
(% Rejections)		31.38%	1.01%	4.25%	6.88%	32.19%	1.42%	3.64%	7.89%
Liquidated	179	48	1	9	13	46	0	3	12
(% Rejections)		26.82%	0.56%	5.03%	7.26%	25.70%	0.00%	1.68%	6.70%
All	1033	297	7	55	57	330	13	42	70
(% Rejections)		28.75%	0.68%	5.32%	5.52%	31.95%	1.26%	4.07%	6.78%

Table 2.10. Conditional Return Smoothing for Subsamples

This table reports the number and percentage of funds having conditional serial correlation, detected by significant positive b1- coefficients evaluated at the two-sided 5% level. The regression model for conditional serial correlation follows Bollen and Pool (2008), i.e. $R_t^O = a + b_1^+ R_{t-1}^O + b_1^-(1 - I_{t-1})R_{t-1}^O + \eta_t$, where R_t^O is the observed gross return in month t and I_{t-1} equals one if the fund's systematic return from an optimal factor model at month t-1 is greater than the mean systematic return. Listed are results when Credit Suisse/Tremont Hedge Fund indices, as well as the asset-based style (ABS) factors developed by Fung and Hsieh (2004) are used as available factors in determining I_{t-1}. Other variables are defined in Table 3, and the high (low) groups consist of funds whose characteristic is greater than or equal to (less than) the median value in the same category. The differences of average return smoothing profiles and smoothing indices for high and low subsamples are reported, with ***, ** and * denoting significance at the 1%, 5%, and 10% levels.

Subsample	Credit Suisse/Tremont Indices				ABS Factors		
	#	%	diff		#	%	diff
High Total Delta	30	6.01%			19	3.81%	
Low Total Delta	22	4.40%	1.61%		21	4.20%	-0.39%
High Mgr Opt Delta	28	5.61%			20	4.01%	
Low Mgr Opt Delta	24	4.80%	0.81%		20	4.00%	0.01%
High Mgr Ownership	34	6.59%			26	5.04%	
Low Mgr Ownership	21	4.06%	2.53%	*	16	3.09%	1.94%
High $ Management Fee	30	5.81%			24	4.65%	
Low $ Management Fee	25	4.84%	0.98%		18	3.48%	1.17%
High Volatility	40	7.75%			22	4.26%	
Low Volatility	15	2.90%	4.85%	***	20	3.87%	0.40%
High Flow (%)	24	4.65%			24	4.65%	
Low Flow (%)	31	6.00%	-1.34%		18	3.48%	1.17%
High Flow Volatility	23	4.46%			25	4.84%	
Low Flow Volatility	32	6.19%	-1.73%		17	3.29%	1.56%
Short Lockup	38	5.58%			29	4.26%	
Long Lockup	17	4.83%	0.75%		13	3.69%	0.57%
Short Redemption Period	39	7.68%			20	3.94%	
Long Redemption Period	16	3.10%	4.58%	***	22	4.26%	-0.33%
Young	30	5.86%			23	4.49%	
Senior	25	4.80%	1.06%		19	3.65%	0.85%
Large Size	30	5.81%			21	4.07%	
Small Size	25	4.84%	0.98%		21	4.06%	0.01%
Graveyard	21	4.3%			18	3.64%	
Live	34	6.3%	-2.06%		24	4.45%	-0.81%

Table 2.11. Conditional Serial Correlation: Cross-Sectional Analysis

This table reports the logit regression in which the dependent variable equals one if a fund features statistically significant conditional serial correlation and zero otherwise. Conditional serial correlation is detected using the regression: $R_t^O = a + b_1^+ R_{t-1}^O + b_1^-(1 - I_{t-1})R_{t-1}^O + \eta_t$, where R_t^O is the observed gross return in month t and I_{t-1} equals one if the fund's systematic return from an optimal factor model at month t-1 is greater than the mean systematic return. Listed are results when Credit Suisse/Tremont Hedge Fund indices, as well as the asset-based style (ABS) factors developed by Fung and Hsieh (2004) are used as available factors in determining I_{t-1}. Independent variables are log(delta), the natural logarithm of the fund's total delta, μ_{GR}, the average gross returns of each fund, $log(\sigma_{GR})$, the natural logarithm of the volatility of gross returns estimated over the calendar year, μ_{flow}, the monthly mean investor cash flow as a percentage of fund assets, $log(\sigma_{Flow})$, the natural logarithm of the volatility of investor cash flows as a percentage of fund assets, $log(RedemptionPeriod)$, the natural logarithm of redemption period in month, Age, the age of funds in months, and Live, an indicator variable that equals one if the fund is live as of April 2010. Dummy variables of broad strategies are defined following Agarwal et al. (2009a). ***, ** and * denote significance at the 1%, 5%, and 10% levels.

	Credit Suisse/Tremont Indices		FH 7-Factor Model	
	Coeff	p-Value	Coeff	p-Value
Intercept	-0.204	0.8971	-0.0459	0.9791
log(delta)	0.1994 *	0.0541	0.2139 *	0.0683
μ_{GR}	-55.5121 **	0.0427	-85.8109 ***	0.0048
log(σ_{GR})	1.1308 ***	0.0002	1.2206 ***	0.0004
μ_{flow}	-3.6574	0.5727	-3.7305	0.5945
log(σ_{flow})	-0.1413	0.6141	0.0387	0.9067
log(RedemptionPeriod)	-0.3980 **	0.0292	0.1449	0.5604
Age	-0.0030	0.3908	-0.0076 *	0.0830
Live	0.4014	0.2000	0.4071	0.2499
Strategy Dummies	Yes		Yes	
LR statistic	25.7435		21.8969	
p-value (LR stat)	0.0071		0.0252	
Adjusted Cox & Snell pseudo-R^2	0.0771		0.0776	
# obs	984		984	
# Reject	51		39	
Frequency	5.18%		3.96%	

Table 2.12. Are Managers of "Return-Smoothing" Funds Paid More Incentive Fees?

This table reports the mean, median and standard deviation of annual dollar incentive fee ($IF) for subgroups of funds based on return smoothing. In Panel A, funds are sorted by return smoothing profile estimates θ_0 in Getmansky et al. (2004b). The smoothing profile is estimated using MA(2) smoothing process $R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}$, under the identification constraint $\theta_0 + \theta_1 + \theta_2 = 1$. The high (low) subgroups consists of funds whose θ_0 is greater than or equal to (less than) the median value in the same strategy category. In Panel B, funds are grouped based on the significance of conditional serial correlation. The conditional serial correlation is defined by significant positive b_1^- in the model defined in Table 2.9. We report the one-sided p-values for the difference between means (Wilcoxon rank-sum test) and for the difference between medians (Median Two-Sample test) of dollar incentive fees. Significant mean or median at 10% level are printed in bold.

Panel A: Subsamples by Unconditional Serial Correlation

Category	Subsample	N	$IF ($'000) Mean	$IF ($'000) Median	$IF ($'000) StdDev	Diff_$IF ($'000) Mean	p-value	Diff_$IF ($'000) Median	p-value
Convertible Arbitrage	Low θ_0	26	1434.56	809.19	1718.01				
	High θ_0	26	2091.03	803.27	3016.25	-656.48	0.32	5.92	0.50
Dedicated Short Bias	Low θ_0	4	571.53	512.91	428.18				
	High θ_0	5	90.39	65.23	75.20	**481.14**	**0.03**	**447.68**	**0.06**
Emerging Markets	Low θ_0	54	3058.03	1273.82	5686.70				
	High θ_0	55	4000.46	887.30	7754.67	-942.42	0.36	386.52	0.20
Equity Market Neutral	Low θ_0	29	1287.87	703.18	2252.10				
	High θ_0	29	1546.60	477.72	3245.65	-258.72	0.47	225.45	0.22
Event Driven	Low θ_0	72	6623.05	2578.39	10382.62				
	High θ_0	73	4892.49	1162.87	12781.68	**1730.56**	**0.00**	**1415.52**	**0.00**
Fixed Income Arbitrage	Low θ_0	27	3679.30	2434.64	4082.80				
	High θ_0	27	4458.86	2178.30	5136.71	-779.56	0.49	256.33	0.39
Global Macro	Low θ_0	26	9790.36	2510.66	14987.08				
	High θ_0	27	8541.26	1867.71	18473.70	1249.10	0.43	642.95	0.45
Long/Short Equity Hedge	Low θ_0	231	3902.70	1462.06	7586.09				
	High θ_0	231	2458.49	887.51	5786.56	**1444.21**	**0.00**	**574.56**	**0.00**
Multi-Strategy	Low θ_0	38	5971.72	2018.54	13536.21				
	High θ_0	38	1956.03	952.02	3448.06	**4015.69**	**0.01**	**1066.52**	**0.09**
Options Strategy	Low θ_0	2	214.79	214.79	51.64				
	High θ_0	3	2167.40	2725.39	1490.13	**-1952.62**	**0.04**	**-2510.60**	**0.09**
All Funds	Low θ_0	511	4109.80	1458.61	8033.20				
	High θ_0	512	3473.01	943.78	8796.24	636.79	0.00	514.83	0.00

Panel B: Subsamples by Significance of Conditional Serial Correlation

Model	Subsample	N	$IF ($'000)			Diff_$IF ($'000)			
			Mean	Median	StdDev	Mean	p-value	Median	p-value
Credit Suisse/Tremont Indices	Significant	55	3655.31	1363.39	7326.00				
	Insignificant	978	3788.43	1148.74	8462.13	-133.12	0.30	214.65	0.10
ABS Factors	Significant	50	2302.44	1243.82	3165.09				
	Insignificant	983	3844.02	1160.68	8548.92	-1541.58	0.47	83.13	0.37

Table 2.13. Unconditional Serial Correlation of Failed Hedge Funds

This table reports the means and standard deviations of the maximum likelihood estimates of the unconditional smoothing profile and smoothing index introduced in Getmansky et al. (2004b), for the subsample of "real failure" hedge funds, where the criteria for real failure" of hedge funds follow Liang and Park (2010), i.e. all three of the following criteria are met, i) once listed in graveyard database ii) negative average rate of return for the last 6 months, and iii) decreased AUM for the last 12 months. The smoothing profile is estimated using MA(2) smoothing process $R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}$, and the smoothing index is defined as $\xi = \theta_0^2 + \theta_1^2 + \theta_2^2$. MA(2) is estimated under the identification constraint $\theta_0 + \theta_1 + \theta_2 = 1$. Difference of the smoothing profiles and smoothing index between the failed funds and other funds in sample are reported, with ***, ** and * denoting significance at the 1%, 5% and 10% levels.

Category	N	θ_0		θ_1		θ_2		ξ	
		Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Convertible Arbitrage	23	0.614	0.179	0.266	0.118	0.120	0.130	0.523	0.188
Dedicated Short Bias	2	0.864	0.035	0.126	0.156	0.009	0.122	0.783	0.022
Emerging Markets	16	0.787	0.104	0.148	0.073	0.065	0.082	0.667	0.149
Equity Market Neutral	13	0.838	0.208	0.045	0.254	0.117	0.167	0.843	0.398
Event Driven	24	0.734	0.151	0.171	0.121	0.095	0.098	0.622	0.212
Fixed Income Arbitrage	15	0.770	0.195	0.197	0.129	0.033	0.159	0.707	0.331
Global Macro	9	1.056	0.293	-0.060	0.192	0.004	0.141	1.245	0.857
Long/Short Equity Hedge	85	0.854	0.236	0.113	0.117	0.032	0.213	0.857	0.723
Multi-Strategy	11	0.762	0.156	0.172	0.107	0.066	0.113	0.659	0.202
Options Strategy	1	0.873	-	0.204	-	-0.077	-	0.810	-
All Failed Funds	199	0.803	0.139	0.139	0.768	0.058	0.147	0.171	0.554
Non-Failed Funds	824	0.852	0.258	0.124	0.171	0.024	0.152	0.860	0.951
Diff		-0.048	***	0.015		0.034	**	-0.689	*

Table 2.14. Conditional Serial Correlation of Failed Hedge Funds

This table reports the frequency counts of funds with significant positive b1- coefficients in the conditional smoothing model of Bollen and Pool (2008) for the subsample of "real failure" hedge funds, where the criteria for "real failure" of hedge funds follow Liang and Park (2010), i.e. all three of the following criteria are met, i) once listed in graveyard database ii) negative average rate of return for the last 6 months, and iii) decreased AUM for the last 12 months. Conditional serial correlation is detected using the regression: $R_t^O = a + b_1^+ R_{t-1}^O + b_1^-(1 - I_{t-1})R_{t-1}^O + \eta_t$, where R_t^O is the observed gross return in month t and I_{t-1} equals one if the fund's systematic return from an optimal factor model at month t-1 is greater than the mean systematic return. Listed are results when Credit Suisse/Tremont Hedge Fund indices, as well as the asset-based style (ABS) factors developed by Fung and Hsieh (2004) are used as available factors in determining I_{t-1}.

Category	# Funds	Credit Suisse/Tremont Indices # Rejections	Credit Suisse/Tremont Indices % Rejections	ABS Factors # Rejections	ABS Factors % Rejections
Convertible Arbitrage	23	4	17.39%	4	17.39%
Dedicated Short Bias	2	0	0.00%	0	0.00%
Emerging Markets	16	1	6.25%	0	0.00%
Equity Market Neutral	14	0	0.00%	0	0.00%
Event Driven	24	1	4.17%	1	4.17%
Fixed Income Arbitrage	16	1	6.25%	1	6.25%
Global Macro	10	0	0.00%	2	20.00%
Long/Short Equity Hedge	86	6	6.98%	4	4.65%
Multi-Strategy	11	1	9.09%	0	0.00%
Options Strategy	1	0	0.00%	0	0.00%
All Failed Funds	203	14	6.90%	12	5.91%

CHAPTER 3

A COMPARISON OF HEDGE FUND GROSS AND NET PERFORMANCE

3.1 Introduction

The incentive contract of hedge funds often feature an annual management fee at about 2% of assets, and a 20% performance (incentive) fee for performance above high-water mark and hurdle rate. The existence of such incentive fees and high-watermark contracts means that hedge fund fees are both time-varying and path-dependent, and therefore that the relationship between gross and net of fee returns is nonlinear.

Net returns have been used for most of the studies on hedge fund performance and risks, and gross returns are rarely calculated and used in the literature due to the availability of data and complexity of algorithm.[1] Some recent studies suggest the necessity of using gross returns for the studies of hedge fund performance and risks. Feng et al. (2010) and Feng and Getmansky (2011) find that gross returns and net returns have significantly different distributions as measured by statistics such as mean, standard deviations, skewness, and kurtosis, as well as return smoothing properties. By modeling gross returns and incentive fees separately in factor models, Brooks et al. (2007) show that the use of net of fee returns can lead to considerably biased estimates of factor exposures which can distort the picture of fund manager performance, due to the non-linear impact of incentive fees.

In this paper, we use the algorithm in Feng et al. (2010) to estimate gross returns, fees and hedge fund deltas. We explore the difference between the gross-of-fee and net-

[1] Only net returns, instead of gross returns, are reported in all major hedge fund databases.

of-fee hedge fund performance, by investigating the difference in distribution, factor exposures and alphas between gross and net returns. We find that gross returns are distributed significantly differently from net returns. The gross-of-fee alphas are higher than the net-of-fee alphas by about 4% annually on average. We also find positive relation between hedge fund performance and fund size, fund flows, and managerial incentives, which holds for both gross-of-fee performance and net-of-fee performance.

The rest of the paper is organized as follows. Section 3.2 gives a review of related literature. Section 3.3 presents the methodology used in the empirical analysis of this paper. Section 3.4 describes the data. Section 3.5 presents the empirical results. Section 3.6 concludes the paper. The algorithm of gross returns and deltas is provided in the Appendix.

3.2 Related Literature

The standard approach to evaluate fund performance is to regress fund returns on risk factors that proxy for different trading strategies. Starting Jensen (1968), linear factor models are widely applied in the studies of fund performance and risks. For mutual fund performance, the Fama and French (1993) three-factor model and Carhart (1997) four-factor model are typically applied. Compared to mutual funds, hedge funds often have more flexibility in their investment, and can apply dynamic trading strategies in various markets. As noted by Fung and Hsieh (1997), hedge fund returns feature option-like payoffs relative to the returns of underlying assets. To capture the option-like features of hedge fund dynamic trading, Fung and Hsieh (2001) develop factors to represent the payoffs of trend-following strategies. Mitchell and Pulvino (2001) generate a return series to represent a risk arbitrate strategy. Agarwal and Naik (2004) use options-based returns to provide a flexible functional form to represent unspecified nonlinear equity strategies.

The "alpha" of factor models is used as a measure of risk-adjusted performance of hedge funds. The majority of research conducted on hedge fund performance finds that hedge funds on average outperform passive benchmarks.[2] However, the findings regarding to the overall trend of hedge fund "alphas" is mixed in the recent literature. Some recent studies suggest that hedge fund alpha has been decreasing over time. Fung et al. (2008) find that hedge fund alphas decrease due to capacity constraints. Zhong (2008) find that on a fund level capital flows have a positive (negative) impact on a funds future performance for smaller (larger) funds. Hence, he confirms the findings of Naik et al. (2007) that fund flows at a strategy level increase the competition within the strategy and exert pressure on the future performance. Ammann et al. (2011) find no evidence of a decreasing hedge fund alpha over time.

Due to the availability of data and complexity of algorithm, gross returns are rarely calculated and used in the literature of hedge fund performance. Some recent studies start to use estimated gross returns in the analysis hedge fund performance, including Brooks et al. (2007), French (2008), Agarwal et al. (2009b), and Feng et al. (2010). Brooks et al. (2007) model gross returns and incentive fees separately, and use the "moneyness" of the call option of incentive fee as a proxy of the delta of incentive contract. They find that the use of net of fee returns can lead to considerably biased estimates of factor exposures which can distort the picture of fund manager performance, due to the non-linear impact of incentive fees. However, their algorithm is based on single-investor assumption, and fund flows are ignored in their estimations. French (2008) also has similar limitations in the algorithm. Agarwal et al. (2009b) provide a comprehensive annual algorithm of incentive fees, gross returns and managerial incentive measures, which takes into account capital flows, high-water mark and hurdle rate provisions of individual investors. Feng et al. (2010) is an extension

[2]See Agarwal and Naik (2000), Fung and Hsieh (2004), Hasanhodzica and Lo (2007), Kosowski et al. (2007), Amenc et al. (2010), and Titman and Tiu (2011).

of the algorithm in Agarwal et al. (2009b), which allows monthly estimation, accrual of incentive fees before they are paid at the end of the year, and modeling both management fee and incentive fee. We will use the algorithm of Feng et al. (2010) in this paper.

3.3 Methodology

While an extensive literature has studied hedge fund performance, there is no consensus so far on which factors to include in a factor model for this purpose. As hedge funds often have flexibilities in their investment, and features option-like non-linear payoffs, factors that captures the non-linearity and the option-like payoff features are used.

In this paper, we estimate the alphas of both gross and net returns for individual hedge funds and hedge fund indices, with two alternative factor models and two different estimation methodologies. The two factor models investigated include the Fung and Hsieh (2004) seven-factor model, and an alternative model that selects the risk factors based on stepwise regression. The factor models are estimated based on a constant-loading OLS approach, and an OLS estimation over rolling 24-month windows.

In the alternative model, we include both the three Fama and French (1993) factors, and the seven asset-based style factors of Fung and Hsieh (2004).[3] The Fama-French factors are the excess return of the market, $MKTRF$, and the returns of the size and value portfolios, SMB and HML. To allow for time variation and non-linearity in the exposure of the size and value premia, the squared returns of the size

[3]These factors are used in many hedge fund performance studies, for example, Bollen and Whaley (2009).

and value portfolios, $SMBSQ$ and $HMLSQ$, are also included.[4] The first two Fung and Hsieh (2004) factors are D10YR, the change in yield of a 10-year Treasury note, and $DSPRD$ (dubbed the "credit spread"), the yield on 10-year BAA corporate bonds less the yield of a 10-year Treasury note. The five remaining Fung-Hsieh variables are trend factors, which are the returns of portfolios of options on bonds, BD; foreign currencies, FX; commodities, COM; short-term interest rates, IR; and stock indexes, STK. To correct for illiquidity, we include both contemporaneous and two lagged months as independent variables.

The excess returns follow

$$R_{i,t} = \alpha_i + \sum_{m=0}^{2} X_{t-m}\beta_{m,i} + \varepsilon_{i,t} \tag{3.1}$$

where $R_{i,t}$ is the excess gross (or net) return of fund (or strategy index) i at time t, and X is a subset of the following factors, $[MKTRF, SMB, HML, SMBSQ, HMLSQ, D10YR, DSPRD, PTFSBD, PTFSFX, PTFSCOM, PTFSIR, PTFSSTK]$. A description of these factors is provided in Table A.1.

Due to limits of degrees of freedom in estimating the model, we attempt to keep the number of factors included in the factor model as low as possible, while still being able to describe the investment opportunities available to hedge funds. Following Agarwal and Naik (2004), Titman and Tiu (2011), and Ammann et al. (2011), we use stepwise regressions for the selection of risk factors to be included in our alternative factor models. For the selection procedure we start with 36 risk factors, including the contemporaneous and first two lags of factors give in X of equation (3.1). For each fund or strategy index, we regress excess gross (or net) returns on the returns of these factors. The stepwise regression approach is based on the Bayesian Information

[4]We follow the Treynor and Mazuy (1966) quadratic regression. We do not add a squared market term since the trend-following factor already captures dynamic exposure to the market.

Criterion (BIC) over the entire sample period with constant coefficients. We employ the identical risk factors for each fund or strategy index over the entire sample period.

The summary of statistics and correlation matrix of the factors used in our analysis are given in Table 4. There are a few high correlations between these factors. For example, the correlation between the Fama-French size factor squared $SMBSQ$, and the Fama-French value factor squared $HMLSQ$, is 0.513, the correlation between the change in the 10-year treasury yield $D10YR$, and the change in the spread between BAA yield and 10-year treasury yield $DSPRD$, is -0.517. As our procedure for selecting factors is based soly on overall explanatory power, it is unaffected by multicollinearity.

3.4 Data

We use the hedge fund data from Lipper TASS database. TASS has monthly net-of-fee returns, assets under management, and other fund characteristics, such as hurdle rates and high-water mark provisions, lockup, notice, and redemption periods, incentive fees, management fees, inception dates, and fund strategies. TASS also classifies hedge funds into 12 strategies: Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity Hedge, Managed Futures, Multi-Strategy, Fund of Funds, and Options Strategy. TASS reports two separate databases, one with "live" funds and another with "graveyard" funds, which keeps track of funds that stop reporting and starts in 1994. Our sample period extends from January 1994 to April 2010. We include both live and graveyard databases and focus on the post-1994 period to mitigate the potential survival-ship bias. As of April 2010, there are 14,177 hedge funds, out of which 5,989 are operational, while 8,188 became defunct during our sample period.

We exclude funds that i) report gross returns, ii) have missing information on management fee or incentive fee,[5] iii) do not report continuously and monthly, and iv) are in the categories of funds of funds, or managed futures, or "other" hedge funds, or have missing strategy information.[6] We delete observations that are backfilled to eliminate backfill bias.[7]

There are additional steps we take to obtain a continuous track of the assets under management (thereafter, AUM) and net asset value (thereafter, NAV) for the algorithm of gross returns and managerial incentives. We delete observations with missing or stale AUM at the beginning or the end of the fund performance history.[8] We also interpolate the missing or stale AUM for up to 3 months, and then keep the longest continuous interval of each fund. As we estimate alpha based on rolling 24-month window regeressions, we require at least 24 non-backfilled return observations for a fund to be included in our analysis.

After these data cleaning steps, we have 2,956 funds in our sample, out of which 1,306 are live funds and 1,650 are graveyard funds. The number of funds in each category of live and graveyard databases is given in Table 3.1.

We also construct equally-weighted and value-weighted strategy index for each category of funds included in our sample. For funds to be included in the equally-weighted strategy index, we additionally require their assets under management to exceed USD 5 million at least once during their non-backfilled observations. After all these adjustments, we are left with a sample of 2816 hedge funds for all analyses

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[5]If both rates are reported zero, then the fund is also eliminated from the sample.

[6]We exclude funds of funds since it has different fee structure from other fund strategies, see Brown et al. (2004). We exclude managed futures and "other" hedge funds since these categories are not usually considered "typical" hedge funds.

[7]The observation is defined as backfilled if the performance date is before "DateAddedToTass"

[8]Asset Under Management is defined as missing if it is not reported or reported as zero; it is defined as stale if it is equal to its value of previous month.

conducted on the equally weighted index and 2956 funds for all analyses conducted on the value-weighted index, where the 5 million assets under management requirement is not imposed.

AUM[9] and NAV are converted to US dollar, if the original currency is not US dollar. The monthly exchange rates and the three-month London Interbank Offered Rate (LIBOR) of US dollar are downloaded from Bloomberg. The data of trend following factors of Fung and Hsieh (2001) are downloaded from David A. Hsieh's website,[10] and the other factors used in Fung and Hsieh (2001) are downloaded from Kenneth French's website. [11]

3.5 Empirical Results

3.5.1 Return Distribution Comparison

In this section, we compare the performance distribution using gross returns with those using net returns. The gross returns are estimated with the algorithm of Feng et al. (2010).[12]

Table 3.3 summarizes the descriptive statistics of gross returns and net returns, for all funds and each category from January 1994 through April 2010. We compare the mean, median, standard deviation, skewness, kurtosis, autocorrelation, Sharpe ratios, and Jarque-Bera normality test between gross returns and net returns. We find that the differences of all these statistics between gross and net returns are significant at the 1% level for funds in both live and graveyard fund database.

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[9] "EstimatedAssets" in TASS

[10] `http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls`

[11] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html`

[12] The details of the algorithm are provided in the Appendix.

As shown in Table 3.3, for all of the ten hedge fund styles, gross returns and net returns are significantly different at significance level of 1% for both mean and median. The difference in the mean monthly return between gross and net returns ranges from 0.252% (amount to 3.07% annually, for Equity Market Neutral) to 0.410% (amount to 5.03% annually, for Emerging Markets). We also find that the mean and median returns of live funds are higher than those of the graveyard funds, indicating that live funds have better overall performance compared to the graveyard funds. For all hedge fund styles, we find that the standard deviations of gross returns are significantly higher (at 1% level) than those of net returns. As the magnitude in the difference in mean returns dominates that of the standard deviation of returns, both measures of Sharpe ratios show significantly higher values for gross returns compared to net returns.[13]

Consistent with the findings in hedge fund literature, Table 3.3 also shows significant deviation from normal distribution for both gross and net returns. Both measures of returns feature negative skewness and high kurtosis, with over half of the funds rejecting the Jarque-Bera normality test. When comparing gross returns with net returns, we find gross returns are less negatively skewed, less leptokurtic, and less likely to reject the normality test. Therefore, gross returns are slightly more "normal-like" than net returns. This may be explained by the asymmetric fee structure of hedge funds, which increases the non-normality of the net return distribution.

Finally, we estimate and compare the first order serial correlation of gross returns and net returns. Consistent with the Feng and Getmansky (2011), we find that live funds have higher serial correlation compared to graveyard funds. Only graveyard funds have significantly higher serial correlation in gross returns than in net returns. We also estimate both the standard and smoothing adjusted Sharpe ratios of both

[13]We estimate both the standard Sharpe ratio and the smoothing-adjusted Sharpe ratio following Lo (2002).

gross returns and net returns, and find that for all fund styles, gross returns are significantly higher in both measures of Sharpe ratios than net returns. The average difference in smoothing-adjusted Sharpe ratio between the two return measures is 0.210, which is about 25% of the Sharpe ratio of net returns.

In summary, the gross returns and net returns of hedge funds have significantly different distributions as measured by all the statistics reported. Therefore, it is important to study the gross-of-fee and net-of-fee performance of hedge funds separately.

3.5.2 Factor Exposure

In Table 3.5, we report the summary of factor exposures for both the Fung and Hsieh (2004) seven-factor model, and the alternative factor model based on stepwise regression, using both gross returns and net returns. We apply these models on both individual funds, as well as the equally-weighted and value-weighted strategy indices.

As reported in Panel A of Table 3.5, only $MKTRF$, $DSPRD$ and $PTFSFX$ have significant average exposures for both individual funds and two indices. the risk exposure to SMB is only significant for estimates of the two indices, and the exposure to $PTFSCOM$ is only significant for individual funds. These results imply that both gross-of-fee and net-of-fee hedge fund performance have significant exposure to the market risk, credit spread, and the trend-following strategy on foreign currency and commodity, as well as the size factor at the strategy level.

Comparing the factor exposures between gross returns and net returns, we find that gross returns produce significantly higher exposures to four of the seven factors, which are $MKTRF$, SMB, $PTFSBD$, and $PTFSCOM$.[14]

We also summarize the factor exposures estimated from the alternative model based on stepwise regression. As reported in Panel B of Table 3.5, the average number

[14]The exposure to Primitive trend follower strategy bond, $PTFSBD$, is negative for both gross return and net return. The exposure estimated using gross returns is larger in magnitude.

of factors are 14 among individual hedge funds (for both gross and net returns), 11 for equally-weighted index (for both gross and net returns), and 8 (9) for value-weighted index using gross (net) returns, respectively. We also find that 73.1% (73.5%) of funds have exposure to the market risk using gross (net) returns. About 40% of funds also have exposure to the lag value of market risk factor. The other factors with more than 40% of funds having exposure to include the size and book-to-market factors, the term and credit spreads, and the trend-following strategies of short-term interest rate and stock. The percentage of funds with other factor exposures range between 35% to 40%. The average factor exposures of gross returns and net returns are also different. The difference is present in the exposure to both contemporaneous and lag values of these values of factors, which implies that the non-linear exposures to these factors are also different between gross and net returns.

In summary, the factor exposures are significantly different for 5 out of 7 factors in the Fung and Hsieh (2004) model, and also different for both contemporaneous and lagged values of factors in the alternative model based on stepwise regression. These results is consistent with the findings of Brooks et al. (2007) in that the factor exposures of gross-of-fee and net-of-fee hedge fund performance are different. The use of net returns can lead to considerably biased estimates of factor exposures which can distort the picture of fund manager performance, due to the non-linear impact of incentive fees.

3.5.3 Alphas of Gross-of-fee and Net-of-fee Performance

In this section, we explore the risk-adjusted gross-of-fee and net-of-fee hedge fund performance as measured by the "alphas" of individual funds and strategy indices estimated from the two models that we use.

Table 3.6 reports the average alphas of individual hedge funds within each strategy, live and dead databases, and the whole sample. Using Fung and Hsieh (2004) seven-factor model, we find the alphas are significantly positive for all strategies, both live and dead databases, and the whole sample. This holds for both gross returns and net returns. This is also consistent with the hedge fund literature that hedge funds have positive risk-adjusted performance. We also find that the live funds have higher alphas than graveyard funds for both gross returns and net returns across all models. The percentage of funds with positive alphas are higher for live funds than for graveyard funds across all models.

Furthermore, we find that gross returns generate significantly higher alphas compared to net returns. On average, gross returns have significantly higher alphas than net returns, for almost all the hedge fund strategies in all models. This difference ranges from 3.36% to 4.2% per year across models and estimation methods. This difference is also higher for the live fund sample, compared to the graveyard sample, which can be explained by the better compensation to live funds than the graveyard funds. Using gross returns, we also find much higher percentage of funds with positive alphas in our models. For example, using Fung and Hsieh (2004) seven-factor model with constant loadings, we find 41% of funds have positive alphas using gross returns, while only 28% of funds have positive alphs using net returns. The difference in this percentage is around 10% using other models.

Finally, we compare the alphas of gross and net returns using equally-weighted indices of hedge fund strategies. As reported in Table 3.7, the results are similar to what we find for individual funds. The alphas of gross returns and net returns are both significantly positive for almost all strategies and models, and gross returns are higher in alphas than net returns by 3.84% to 5.76% annually, depending on the model that we use.

In summary, we find that on average, the gross-of-fee alpha is higher than the net-of-fee alpha by about 4% annually, and the percentage of funds with significantly positive gross-of-fee alpha is higher than the precentage of funds with significantly positive net-of-fee alpha by about 10%. Our findings suggest that the gross-of-fee hedge fund performance is significantly better than the net-of-fee hedge fund performance.

3.5.4 More on the Hypotheses about Hedge Fund Alphas

In this section, we investigate several hypotheses regarding hedge fund performance that have been tested in literature, using both gross returns and net returns. We are interested in whether there is a decrease of alpha over time, whether there is capacity constraint for hedge fund performance, and the relation between hedge fund performance and managerial incentives. The description and summary statistics of fund characteristics, such as AUM and fund flows, and the managerial incentives are reported in Table 3.2.

3.5.4.1 Is Alpha Decreasing Over Time?

We estimate time series of alphas for both gross returns and net returns using rolling-window regression. The result from Fung and Hsieh (2004) seven-factor model is plotted in Figure 1. We find that alpha of hedge funds are positive almost all the time, for both gross-of-fee performance and net-of-fee performance. There is no evidence that hedge fund alpha is decreasing over time.

3.5.4.2 Is there Capacity Constraint in Hedge Fund Performance?

We investigate whether capacity constraint holds for gross-of-fee and net-of-fee performance of hedge funds, by examining the average alphas in quintiles of fund size and fund flows.

As reported in Panel A of Table 3.8, the difference between alphas of the top and bottom quintiles of fund size is significantly positive, using both gross returns and net returns. Similar result holds for flow quintiles. These results imply that larger fund size and fund flows are associated with better performance, and do not support that there is capacity constraint for hedge funds performance in our sample.

3.5.4.3 Relation Between Hedge Fund Performance and Managerial Incentives

We examine the relation between hedge fund performance and managerial incentives using two incentive measures, which are the total delta as introduced by Agarwal et al. (2009b) and the indicator of high-water mark provision.[15]

As reported in Table 3.8, we find that the funds with higher delta or high-water mark provision tend to perform better, which holds for both gross returns and net returns. This result implies that hedge funds with higher managerial incentives tend to have better gross-of-fee and net-of-fee risk-adjusted performance.

3.6 Conclusion

Previous literature suggests that the factor exposures may be biased when estimated using net returns, due to the non-linear incentive structure of hedge funds. In this paper, we explore whether and how the risk-adjusted hedge fund performance is different using gross-of-fee and net-of-fee measures. We employ both Fung and Hsieh (2004) seven-factor model and an alternative factor model based on stepwise regression, and use both constant-loading regression and rolling-window regression for this purpose. We document several interesting findings:

First, the gross return distribution is significantly different from that of the net returns. This holds for statistics like mean, median, standard deviation, skewness and kurtosis, as well as return smoothing properties. We also find that gross returns are more "normal-like" compared to net returns, due to the asymmetric fee structure which adds non-normality to the net return distribution.

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[15]See the definition and algorithm of total delta in the Appendix.

Second, the risk-adjusted performance is different between gross-of-fee and net-of-fee measures. Both standard and smoothing-adjusted Sharpe ratios are higher for gross returns than for net returns. The alphas of all factor models are also significantly higher for gross returns than for net returns, and the average difference in alpha is about 4% per year.

Finally, we find no evidence of decrease in alpha or capacity constraint in hedge fund performance for both gross-of-fee and net-of-fee measures. We also find a positive relation between hedge fund alphas and the managerial incentives, which also holds for both gross-of-fee and net-of-fee measures.

In summary, the performance distribution of hedge funds is significantly different before and after applying fees, due to the non-linear fee structure of hedge funds. The gross-of-fee risk-adjusted performance of hedge funds is much higher than the net-of-fee measure. Our findings suggest that it is necessary to examine the gross-of-fee performance of hedge funds separately from the net-of-fee performance, which may give us a clearer picture of the risk structure and performance of hedge fund portfolios.

Table 3.1. Number of Funds in the TASS Hedge Fund Live and Graveyard Databases

In this table we report the number of hedge funds in TASS database having at least 24 months of continuous, non-backfilled return history in our sample, from January 1994 to April 2010.

Strategy	Code	Number of Funds Combined	Live	Graveyard
Convertible Arbitrage	CA	139	35	104
Dedicated Short Bias	DSB	22	7	15
Emerging Markets	EM	324	213	111
Equity Market Neutral	EMN	244	74	170
Event Driven	ED	345	119	226
Fixed Income Arbitrage	FIA	141	43	98
Global Macro	GM	182	75	107
Long/Short Equity Hedge	LSEH	1330	604	726
Multi-Strategy	MS	216	124	92
Options Strategy	OS	13	12	1
All		2956	1306	1650

Table 3.2. Statistics of Fund Characteristics, Flow, and Managerial Incentives

This table reports summary statistics of fund characteristics, capital flows and managerial incentives for funds in our sample from January 1994 to April 2010. Panel A show statistics for all funds, and panel B show statistics for each category. *Total Delta* is the total expected dollar change in the manager's wealth for a 1% change in NAV. *Mgr's Opt Delta* is the delta from incentive contracts. *Mgr Ownership* is the percentage of manager's investment in the fund to the total asset under management. *Flow* is the annual capital flow scaled by the previous end-of-year AUM, reported in percentage. *$MF* and *$IF* are the annual dollar amount of management fee and the annual dollar amount of incentive fees respectively, reported in million US dollars. *LockUpPeriod* is lockup period in years based on funds that have nonzero lockup period. *RedemptionPeriod* is the sum of RedemptionNoticePeriod and RedemptionFrequency, reported in years. *Age* is age of funds in years. *AUM* is the monthly average of fund asset under management, given as millions of US dollars. *MF (%)* and *IF (%)* the percentage rates of management fee and incentive fee respectively. In Panel B, all variables are reported in mean.

Panel A: All Funds

Variable	N	Mean	StdDev	Min	Median	Max
Age (year)	2956	7.28	4.02	2.08	6.17	32.42
AUM ($ million)	2956	153.16	341.58	0.02	49.60	5981.84
MF (%)	2956	1.40	0.49	0.00	1.50	6.00
IF (%)	2956	18.88	4.47	0.00	20.00	50.00
LockUpPeriod (year)	958	1.05	0.57	0.08	1.00	7.50
RedemptionPeriod (year)	2956	0.31	0.24	0.00	0.25	1.50
Flow (Ann. %)	2596	216.39	477.22	-19.12	49.65	789.46
$MF ($ million)	2596	1.72	1.15	0.40	1.61	3.28
$IF ($ million)	2596	2.79	2.94	0.35	2.02	7.19
Total Delta ($ million)	2868	0.28	0.17	0.10	0.25	0.52
Mgr's Opt Delta ($ million)	2868	0.18	0.11	0.06	0.16	0.33
Mgr Ownership (%)	2868	5.80	5.73	0.03	4.18	19.77

Panel B: By Strategy

Strategy	N	Age (year)	AUM ($MM)	MF (%)	IF (%)	LockUp Period (year)	Redemption Period (year)	Flow (Ann. %)	$MF ($MM)	$IF ($MM)	Total Delta ($MM)	Mgr's Opt Delta ($MM)	Mgr Owner-ship (%)
CA	139	7.76	193.96	1.41	18.67	1.02	0.32	579.50	2.40	3.33	0.38	0.28	4.99
DSB	22	7.87	35.44	1.36	18.30	0.76	0.29	30.65	0.40	0.61	0.05	0.03	6.70
EM	324	6.94	118.85	1.61	17.92	1.10	0.26	23.93	1.46	2.64	0.22	0.12	7.59
EMN	244	6.54	98.28	1.36	19.08	0.98	0.22	41.97	1.10	1.06	0.14	0.11	3.87
ED	345	8.26	269.77	1.40	19.01	1.22	0.48	36.32	3.32	5.40	0.51	0.35	4.70
FIA	141	7.36	203.78	1.39	19.90	0.79	0.30	28.24	2.23	3.03	0.40	0.27	5.78
GM	182	6.60	188.05	1.57	18.91	1.08	0.19	196.68	2.13	3.83	0.38	0.20	5.70
LSEH	1330	7.32	121.43	1.31	19.14	1.01	0.31	351.98	1.18	2.30	0.22	0.14	6.15
MS	216	6.92	201.97	1.60	17.79	1.15	0.29	89.96	2.57	2.79	0.32	0.21	5.38
OS	13	7.57	103.26	1.50	19.23	0.42	0.23	42.59	1.18	1.80	0.16	0.11	5.62

Table 3.3. Summary Statistics: Gross Return vs Net Return

Listed are summary statistics of both gross and net returns of hedge funds in TASS combined database with at least 24 months of continuous, non-backfilled return history from January 1994 to April 2010. Both gross returns (GR) and net returns (NR) are used in the computation of all statistics. The *mean*, *median*, and standard deviation (*StdDev*) of monthly returns are reported in percentage. Skew measures skewness, and Kurt measures excess kurtosis, i.e. the fourth moment around the mean divided by the square of the variance of the probability distribution minus 3. The difference of statistics between gross returns and net returns are reported, with ***, ** and * denoting significance of t test at the 1%, 5%, and 10% levels. We also reported the first order serial correlations (ρ_1), the Sharpe ratios calculated both using the standard method (SR) and the smoothing-adjusted method (SR*) in Lo (2002), and the percentage of funds that reject Jarque-Bera normality test at the 10% level.

Category	N		Mean (%)	Median (%)	StdDev (%)	Skew	Kurt	ρ_1	SR	SR*	JB (% Rejection)
		GR	0.777	0.908	2.959	-0.632	4.810	0.387	1.765	1.238	0.626
CA	139	NR	0.501	0.669	2.719	-0.792	5.301	0.385	1.460	0.997	0.647
		diff	0.277 ***	0.239 ***	0.240 ***	0.159 ***	-0.492 ***	0.002	0.305 ***	0.241 ***	-0.022
		GR	0.648	0.041	7.019	0.421	0.743	0.119	0.376	0.373	0.409
DS	22	NR	0.289	-0.084	6.299	0.264	0.475	0.117	0.201	0.212	0.318
		diff	0.359 ***	0.125 ***	0.720 ***	0.157 ***	0.269 ***	0.002	0.175 ***	0.161 ***	0.091
		GR	1.137	1.376	7.411	-0.409	3.487	0.237	0.732	0.652	0.611
EM	324	NR	0.727	1.091	6.912	-0.571	3.923	0.238	0.551	0.511	0.645
		diff	0.410 ***	0.284 ***	0.499 ***	0.162 ***	-0.436 ***	-0.001	0.181 ***	0.141 ***	-0.034 ***
		GR	0.682	0.708	3.050	-0.229	3.446	0.091	1.013	1.066	0.451
EMN	244	NR	0.430	0.509	2.751	-0.359	3.588	0.085	0.765	0.811	0.484
		diff	0.252 ***	0.199 ***	0.299 ***	0.129 ***	-0.142 ***	0.006 ***	0.248 ***	0.255 ***	-0.033 **
		GR	0.913	1.022	3.166	-0.481	3.802	0.239	1.860	1.451	0.733
ED	345	NR	0.611	0.762	2.855	-0.646	4.350	0.234	1.590	1.223	0.748
		diff	0.302 ***	0.260 ***	0.311 ***	0.165 ***	-0.548 ***	0.004 ***	0.270 ***	0.228 ***	-0.014
		GR	0.686	0.873	3.184	-1.242	9.271	0.222	2.874	2.253	0.759
FIA	141	NR	0.411	0.632	2.947	-1.414	10.189	0.218	2.479	1.893	0.752
		diff	0.275 ***	0.241 ***	0.237 ***	0.171 ***	-0.918 ***	0.004 **	0.395 ***	0.360 ***	0.007
		GR	0.936	0.681	4.588	0.266	2.149	0.062	0.856	0.948	0.505
GM	182	NR	0.604	0.463	4.084	0.150	2.134	0.061	0.647	0.720	0.495
		diff	0.332 ***	0.218 ***	0.505 ***	0.116 ***	0.014	0.001	0.209 ***	0.228 ***	0.011
		GR	0.973	0.953	5.261	0.015	1.933	0.123	0.807	0.859	0.495
LSEH	1330	NR	0.646	0.723	4.778	-0.120	2.082	0.122	0.629	0.684	0.527
		diff	0.327 ***	0.230 ***	0.483 ***	0.134 ***	-0.149 ***	0.002 ***	0.179 ***	0.175 ***	-0.032 ***

Table 3: Summary Statistics: Gross Return vs Net Return (Cont'd)

Category	N		Mean (%)	Median (%)	StdDev (%)	Skew	Kurt	ρ_1	SR	SR*	JB (% Rejection)
		GR	0.858	0.931	4.185	-0.314	3.506	0.203	1.671	1.614	0.625
MS	216	NR	0.551	0.671	3.869	-0.457	3.822	0.202	1.340	1.290	0.676
		diff	0.307 ***	0.260 ***	0.317 ***	0.144 ***	-0.316 ***	0.001	0.330 ***	0.323 ***	-0.051 **
		GR	0.967	1.059	3.869	-0.327	9.197	0.225	1.043	0.981	0.923
OS	13	NR	0.659	0.828	3.495	-0.419	8.969	0.223	0.831	0.786	0.923
		diff	0.307 ***	0.230 ***	0.374 ***	0.091 *	0.228	0.001	0.212 ***	0.195 ***	0.000
		GR	0.984	1.081	5.173	-0.265	2.941	0.204	0.880	0.816	0.617
Live	1306	NR	0.653	0.833	4.780	-0.404	3.291	0.204	0.680	0.645	0.648
		Diff	0.330 ***	0.248 ***	0.394 ***	0.139 ***	-0.350 ***	0.000	0.200 ***	0.171 ***	-0.031 ***
		GR	0.876	0.858	4.414	-0.162	3.196	0.136	1.357	1.261	0.519
Graveyard	1650	NR	0.563	0.626	3.979	-0.308	3.414	0.132	1.113	1.020	0.540
		Diff	0.314 ***	0.231 ***	0.435 ***	0.146 ***	-0.218 ***	0.004 ***	0.244 ***	0.241 ***	-0.021 ***
		GR	0.924	0.956	4.749	-0.207	3.083	0.166	1.146	1.064	0.562
All	2956	NR	0.603	0.718	4.333	-0.350	3.360	0.164	0.922	0.854	0.588
		Diff	0.321 ***	0.238 ***	0.417 ***	0.143 ***	-0.276 ***	0.002 ***	0.225 ***	0.210 ***	-0.025 ***

Table 3.4. Statistics and Correlation Matrix of Factors Used to Analyze Reported Hedge Fund Returns

Listed are summary statistics (Panel A) and correlation matrix (Panel B) of factors used to analyze reported hedge fund returns. The mean, median, and standard deviation (StdDev) of factor returns are reported in percentage. Skew measures skewness, and Kurt measures excess kurtosis, i.e. the fourth moment around the mean divided by the square of the variance of the probability distribution minus 3. We also reported the Sharpe ratios calculated using the standard method (SR). Data are from January 1994 to April 2010. See Appendix Table A.1 for definitions of factors.

	Correlation Matrix											
	MKTRF	SMB	HML	SMBSQ	HMLSQ	D10YR	DSPRD	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK
MKTRF	1.000											
SMB	0.223	1.000										
HML	-0.268	-0.380	1.000									
SMBSQ	0.063	0.310	-0.233	1.000								
HMLSQ	-0.192	0.140	0.076	0.513	1.000							
D10YR	0.125	0.176	-0.114	-0.081	-0.079	1.000						
DSPRD	-0.443	-0.253	0.090	0.067	0.040	-0.517	1.000					
PTFSBD	-0.170	-0.044	-0.051	0.058	0.041	-0.169	0.176	1.000				
PTFSFX	-0.178	-0.008	0.025	-0.003	-0.106	-0.135	0.283	0.229	1.000			
PTFSCOM	-0.160	-0.042	-0.030	0.005	-0.082	-0.119	0.223	0.211	0.378	1.000		
PTFSIR	-0.294	-0.110	-0.006	-0.048	-0.023	-0.092	0.408	0.199	0.291	0.306	1.000	
PTFSSTK	-0.192	-0.110	0.106	-0.068	-0.032	-0.204	0.308	0.169	0.223	0.111	0.298	1.000
Mean (%)	0.479	0.233	0.341	0.138	0.125	-1.092	0.224	-1.600	-0.048	-0.492	2.835	-4.737
StdDev (%)	4.640	3.723	3.523	0.431	0.263	28.103	22.589	14.753	19.693	13.858	28.715	12.738
Skew	-0.866	0.848	-0.033	8.640	4.204	0.020	1.428	1.451	1.407	1.294	4.132	0.994
Kurt	1.489	7.739	2.590	86.030	20.927	1.184	11.749	3.088	2.830	2.714	23.449	2.008
SR	0.358	0.217	0.336	1.112	1.641	-0.135	0.034	-0.376	-0.009	-0.123	0.342	-1.288

Table 3.5. Summary Statistics of Factor Exposure

This table reports the statistics of the factor exposure, estimated using both gross returns (GR) and net returns (NR) of individual hedge funds in the TASS database that has at least 24 months of continuous, non-backfilled history from January 1994 to April 2010. The two factor models investigated include the Fung and Hsieh (2004) seven-factor model (FH) and a factor model that selects the risk factors based on stepwise regression. Panel A reports the average factor exposure of the Fung and Hsieh (2004) seven-factor model, using returns of both individual funds and strategy indices. Panel B reports the results of the the factor model based on stepwise regression, where Panel B1 reports the regression statistics and Panel B2 reports the percentage of funds with factor exposures and the average factor exposures. See Table A.1 for a description of factors used in the models.

Panel A: Average Factor Exposure of Fung and Hsieh (2004) Seven-factor Model

Factor		Individual Funds		Equally-weighted index		Value-weighted index	
MKTRF	GR	0.3308	***	0.3199	***	0.3056	***
	NR	0.3068	***	0.2941	***	0.2812	***
	diff	0.0239	***	0.0258		0.0244	
SMB	GR	0.0093		0.1464	***	0.1490	*
	NR	-0.0003		0.1255	***	0.1334	*
	diff	0.0096	***	0.0209		0.0157	
D10YR	GR	-0.0052	***	-0.0021		-0.0125	
	NR	-0.0053	***	-0.0028		-0.0121	*
	diff	0.0001		0.0007		-0.0004	
DSPRD	GR	-0.0243	***	-0.0228	***	-0.0223	***
	NR	-0.0235	***	-0.0236	***	-0.0221	***
	diff	-0.0008	***	0.0008		-0.0002	
PTFSBD	GR	-0.0025		-0.0024		-0.0080	
	NR	-0.0023		-0.0032		-0.0080	
	diff	-0.0003	*	0.0008		0.0001	
PTFSFX	GR	0.0093	***	0.0130	*	0.0282	**
	NR	0.0085	***	0.0113	*	0.0245	**
	diff	0.0008	***	0.0017		0.0037	
PTFSCOM	GR	0.0038	***	0.0053		0.0032	
	NR	0.0021		0.0037		0.0025	
	diff	0.0018	***	0.0016		0.0007	

Panel B1: Statistics of Factor Model based on Stepwise Regression

	Individual Funds		Equally-weighted index		Value-weighted index	
	GR	NR	GR	NR	GR	NR
No. of funds	2956	2956	2816	2816	2956	2956
Adjusted-R2	0.61	0.62	0.61	0.64	0.29	0.31
No. of factors	14	14	11	11	8	9

Panel B2: Factor model based on stepwise regression

Factor	Funds w. Factor Exposure (%)		Average Factor Exposure	
	Gross Return	Net Return	Gross Return	Net Return
MKTRF	73.1%	73.5%	0.4622	0.3939
SMB	47.4%	47.4%	0.1090	0.0392
HML	47.3%	47.3%	-0.1210	-0.0844
SMBSQ	37.8%	37.8%	-3.3254	-1.7638
HMLSQ	36.9%	37.9%	-1.7570	-2.0944
D10YR	43.2%	43.8%	-0.0138	-0.0128
DSPRD	47.2%	49.2%	-0.0397	-0.0429
PTFSBD	38.0%	38.4%	0.0216	0.0138
PTFSFX	35.8%	35.7%	0.0142	0.0073
PTFSCOM	36.8%	37.0%	0.0476	0.0384
PTFSIR	49.8%	49.0%	-0.0246	-0.0253
PTFSSTK	44.5%	44.1%	0.0657	0.0497
lag_mktrf	40.3%	40.1%	0.1508	0.1100
lag_SMB	35.6%	35.7%	-0.0226	-0.0232
lag_HML	34.9%	35.4%	0.1084	0.1274
lag_SMBSQ	35.4%	35.2%	-1.3630	-1.7415
lag_HMLSQ	39.1%	39.3%	-2.7175	-2.4134
lag_D10YR	35.2%	34.8%	-0.0077	-0.0043
lag_DSPRD	37.2%	37.8%	-0.0082	-0.0019
lag_PTFSBD	33.9%	33.8%	-0.0276	-0.0145
lag_PTFSFX	35.4%	35.0%	0.0116	0.0066
lag_PTFSCOM	33.4%	33.5%	0.0240	0.0100
lag_PTFSIR	36.4%	36.9%	0.0033	0.0052
lag_PTFSSTK	35.5%	35.5%	0.0179	0.0184
lag2_mktrf	39.6%	39.6%	0.1367	0.1168
lag2_SMB	35.7%	36.0%	-0.0352	-0.0211
lag2_HML	38.2%	39.6%	-0.1660	-0.1352
lag2_SMBSQ	35.1%	35.0%	-0.4939	-2.1102
lag2_HMLSQ	38.9%	38.5%	-0.6075	-0.8493
lag2_D10YR	34.3%	34.6%	0.0100	0.0084
lag2_DSPRD	36.3%	36.2%	-0.0131	-0.0099
lag2_PTFSBD	37.6%	37.4%	0.0248	0.0113
lag2_PTFSFX	35.9%	35.4%	0.0020	0.0054
lag2_PTFSCOM	35.3%	35.8%	0.0010	-0.0082
lag2_PTFSIR	35.9%	36.1%	-0.0128	-0.0131
lag2_PTFSSTK	36.8%	35.6%	-0.0264	-0.0238

Table 3.6. Average Alphas of Individual Funds within Each Strategy

This table reports alpha estimated with two alternative factor models, and two different estimation methodologies for 10 different hedge fund strategies and the whole sample. The two factor models investigated include the Fung and Hsieh (2004) seven-factor model (FH) and a factor model that selects the risk factors based on stepwise regression. The factor models are estimated based on a constant-loading OLS approach, and an OLS estimation over rolling 24-month windows. The table is based on both gross returns (GR) and net returns (NR) of funds with at lest 24 continuous non-backfilled observations in the TASS database from January 1994 and April 2010. N indicates the number of funds in each sample. For rolling OLS the first 23 observations of each fund are lost for estimating the first alpha. The column sign. a reports the proportion of funds in the respective strategies that exhibit an alpha that is greater than zero at a 5% significance level (based on Newey-West standard errors) based on the constant factor loading OLS regression and the column sign.α_{roll} reports the proportion of funds that have a significantly positive average alpha over time when estimating the alpha over 24 months with rolling regression. All alphas are expressed in monthly percentage returns, with *, **, and *** denoting significance levels (two-sided) at 10%, 5% and 1% based on Newey-West standard errors.

			Fung and Hsieh (2004)							Stepwise Regression						
Category	N		α_{OLS}		Adj_R2	α_{roll}		Sign. α(%)	Sign. α_{roll} (%)	α_{OLS}		Adj_R2	α_{roll}		Sign. α(%)	Sign. α_{roll} (%)
		GR	0.54	***	0.25	0.48	***	40	75	0.14		0.54	0.28	***	23	70
CA	139	NR	0.27	***	0.25	0.24	***	24	63	0.16		0.52	0.14	***	11	59
		diff	0.27	***		0.24	***			-0.02			0.15	***		
		GR	0.71	***	0.63	0.62	***	41	68	1.36	*	0.77	0.45	***	29	71
DSB	22	NR	0.33	*	0.62	0.33	***	23	50	-0.01		0.77	0.23	**	18	65
		diff	0.38	***		0.29	***			1.37			0.22	***		
		GR	0.88	***	0.35	1.02	***	40	65	1.77	**	0.65	1.15	***	43	77
EM	324	NR	0.49	***	0.36	0.64	***	29	56	0.80		0.64	0.81	***	31	71
		diff	0.40			0.38	***			0.97	***		0.34	***		
		GR	0.45	***	0.16	0.49	***	35	63	0.67	***	0.55	0.56	***	28	74
EMN	244	NR	0.19	***	0.16	0.25	***	25	54	0.36	*	0.58	0.32	***	22	62
		diff	0.25	***		0.24	***			0.31	**		0.24	***		
		GR	0.59	***	0.30	0.68	***	54	79	0.69	***	0.60	0.64	***	46	80
ED	345	NR	0.30	***	0.31	0.41	***	40	73	0.51	***	0.59	0.36	***	36	70
		diff	0.29	***		0.28	***			0.18	*		0.28	***		

Table 6: Average Alphas of Individual Funds within Each Strategy (Cont'd)

Category	N		Fung and Hsieh (2004) α_{OLS}		Adj_R2	α_{roll}		Sign. α (%)	Sign. α_{roll} (%)	Stepwise Regression α_{OLS}		Adj_R2	α_{roll}		Sign. α (%)	Sign. α_{roll} (%)
		GR	0.51	***	0.20	0.58	***	53	73	0.38	**	0.60	0.55	***	36	75
FIA	141	NR	0.23	***	0.20	0.30	***	37	63	0.17		0.59	0.27	***	27	67
		diff	0.28	***		0.27	***			0.21	**		0.28	***		
		GR	0.74	***	0.19	0.68	***	40	65	1.27	***	0.56	0.73	***	28	65
GM	182	NR	0.41	***	0.19	0.38	***	29	57	1.06	***	0.54	0.42	***	24	56
		diff	0.33	***		0.30	***			0.21			0.31	***		
		GR	0.67	***	0.33	0.67	***	36	69	0.84	***	0.64	0.71	***	31	71
LSEH	1330	NR	0.37	***	0.34	0.39	***	24	60	0.54	***	0.65	0.44	***	22	63
		diff	0.31	***		0.28	***			0.29	***		0.28	***		
		GR	0.71	***	0.26	0.66	***	50	78	1.14	***	0.60	0.74	***	50	82
MS	216	NR	0.41	***	0.27	0.37	***	37	67	0.74	***	0.61	0.46	***	31	74
		diff	0.30	***		0.30	***			0.39	***		0.29	***		
		GR	0.88	***	0.18	0.74	***	46	85	1.69	*	0.51	0.80	***	33	100
OS	13	NR	0.57	***	0.19	0.44	***	31	77	1.31	*	0.54	0.61	***	33	100
		diff	0.31	***		0.30	***			0.38	**		0.19	***		
		GR	0.89	***	0.34	0.83	***	49	80	1.59	***	0.60	0.94	***	49	84
Live	1306	NR	0.56	***	0.35	0.52	***	34	71	1.13	***	0.61	0.64	***	36	78
		Diff	0.33	***		0.31	***			0.46	***		0.30	***		
		GR	0.49	***	0.26	0.53	***	34	62	0.37	***	0.63	0.46	***	23	65
Graveyard	1650	NR	0.19	***	0.26	0.26	***	24	53	0.11		0.63	0.21	***	16	54
		Diff	0.29	***		0.27	***			0.26	**		0.25	***		
		GR	0.66	***	0.29	0.68	***	41	70	0.91	***	0.61	0.71	***	35	74
All	2956	NR	0.35	***	0.30	0.39	***	28	61	0.56	***	0.62	0.43	***	25	65
		Diff	0.31	***		0.29	***			0.35	***		0.28	***		

Table 3.7. Average Alphas of Equally-Weighted Hedge Fund Strategy Indices

This table reports alpha estimated with two alternative factor models, and two different estimation methodologies for 10 different hedge fund strategies and the whole sample. The two factor models investigated include the Fung and Hsieh (2004) seven-factor model (FH) and a factor model that selects the risk factors based on stepwise regression. The factor models are estimated based on a constant-loading OLS approach, and an OLS estimation over rolling 24-month windows. The table is based on both gross returns and net returns of equally-weighted indices of funds with at lest 24 continuous non-backfilled observations in the TASS database from January 1994 and April 2010. N indicates the number of funds in each sample. For rolling OLS the first 23 observations of each fund are lost for estimating the first alpha. All alphas are expressed in monthly percentage returns, with *, ** and *** denoting significance levels of 10%, 5% and 1% (two-sided) based on Newey-West standard errors. The differences between GR and NR statistics (diff) are reported.

Table 7: Average Alphas of Equally-Weighted Hedge Fund Strategy Indices (Cont'd)

Category		Fung and Hsieh (2004)					Stepwise Regression				
		α_{OLS}		Adj_R2	α_{roll}		α_{OLS}		Adj_R2	α_{roll}	
Convertible Arbitrage	GR	0.66	***	0.61	0.59	***	0.74	***	0.61	0.54	***
	NR	0.37	***	0.63	0.32	***	0.44	***	0.63	0.29	***
	diff	0.29			0.27		0.30			0.25	
Dedicated Short Bias	GR	0.78	***	0.63	0.83	***	0.94	***	0.61	0.88	***
	NR	0.40	***	0.62	0.49	***	0.57	***	0.60	0.58	***
	diff	0.38			0.34		0.37			0.30	
Emerging Markets	GR	0.57	***	0.50	0.57	***	0.70	**	0.45	0.77	***
	NR	0.19	**	0.51	0.22		0.24		0.46	0.45	***
	diff	0.38			0.35		0.46			0.32	
Equity Market Neutral	GR	0.62	***	0.10	0.63	***	0.72	***	0.10	0.75	***
	NR	0.31	***	0.13	0.32	***	0.39	***	0.11	0.44	***
	diff	0.31			0.30		0.33			0.31	
Event Driven	GR	0.68	***	0.44	0.62	***	0.76	***	0.44	0.62	***
	NR	0.37	***	0.48	0.34	***	0.45	***	0.48	0.35	***
	diff	0.30			0.28		0.31			0.27	
Fixed Income Arbitrage	GR	0.54	***	0.46	0.57	***	0.51	***	0.54	0.49	***
	NR	0.23	***	0.48	0.27	***	0.21		0.57	0.20	***
	diff	0.31			0.30		0.30			0.29	
Global Macro	GR	1.03	***	0.26	0.73	***	0.89	***	0.17	0.54	***
	NR	0.64	***	0.26	0.39	***	0.51	**	0.18	0.22	**
	diff	0.39			0.34		0.38			0.33	
Long/Short Equity Hedge	GR	0.79	***	0.75	0.82	***	0.81	***	0.79	0.80	***
	NR	0.45	***	0.78	0.48	***	0.47	***	0.81	0.45	***
	diff	0.34			0.33		0.34			0.35	
Multi-Strategy	GR	0.69	***	0.33	0.63	***	0.60	***	0.31	0.64	***
	NR	0.38	***	0.33	0.32	***	0.35	**	0.29	0.39	***
	diff	0.31			0.31		0.24			0.25	
Options Strategy	GR	0.64	***	0.01	0.81	***	0.48		-0.19	0.67	***
	NR	0.32	**	0.01	0.47	***	0.24		-0.15	0.70	***
	diff	0.32			0.34		0.24			-0.02	
All	GR	0.76	***	0.61	0.68	***	0.86	***	0.62	0.97	***
	NR	0.42	***	0.64	0.36	***	0.48	***	0.65	0.49	***
	diff	0.34			0.32		0.38			0.48	

Table 3.8. Alphas for Subgroups of AUM, Fund Flows and Deltas

This table reports the aveerage alphas for subgroups of hedge funds sorted by AUM, fund flows (scaled by AUM), and total delta, respectively. The two factor models investigated include the Fung and Hsieh (2004) seven-factor model (FH) and a factor model that selects the risk factors based on stepwise regression (Stepwise). The factor models are estimated based on a constant-loading OLS approach. The table is based on both gross returns (GR) and net returns (NR) of funds with at lest 24 continuous non-backfilled observations in the TASS database from January 1994 and April 2010. N indicates the number of funds in each sample. All alphas are expressed in monthly percentage returns. The asterisks *, **, and *** denoting significance levels (two-sided) at 10%, 5% and 1% for the difference between the top and bottom quintile groups.

Panel A: Alphas for Subgroups of AUM

Quintiles of AUM	N	FH Model				Stepwise Model	
		GR		NR		GR	NR
Highest AUM	591	0.8508		0.5200		1.1367	0.8297
2	591	0.7189		0.4182		0.8802	0.5989
3	592	0.6206		0.3170		0.9427	0.5913
4	591	0.6401		0.3327		0.7756	0.4754
Lowest AUM	591	0.4787		0.1800		0.8125	0.3167
Highest - Lowest		0.3722	***	0.3400	***	0.3242	0.5130

Panel B: Alphas for Subgroups of Flow (%)

Quintiles of Flow (%)	N	FH Model				Stepwise Model	
		GR		NR		GR	NR
Highest Flow (%)	591	0.9769		0.6168		1.0674	0.8444
2	591	0.7553		0.4342		1.0132	0.7806
3	592	0.6540		0.3548		0.7787	0.4077
4	591	0.5447		0.2571		0.8680	0.2193
Lowest Flow (%)	591	0.3782		0.1048		0.8208	0.5602
Highest - Lowest		0.5987	***	0.5120	***	0.2466	0.2842

Table 8: Alphas for Subgroups of AUM, Fund Flows and Deltas (Cont'd)

Panel A: Alphas for Subgroups of AUM

Quintiles of AUM	N	FH Model				Stepwise Model	
		GR		NR		GR	NR
Highest AUM	591	0.8508		0.5200		1.1367	0.8297
2	591	0.7189		0.4182		0.8802	0.5989
3	592	0.6206		0.3170		0.9427	0.5913
4	591	0.6401		0.3327		0.7756	0.4754
Lowest AUM	591	0.4787		0.1800		0.8125	0.3167
Highest - Lowest		0.3722	***	0.3400	***	0.3242	0.5130

Panel B: Alphas for Subgroups of Flow (%)

Quintiles of Flow (%)	N	FH Model				Stepwise Model	
		GR		NR		GR	NR
Highest Flow (%)	591	0.9769		0.6168		1.0674	0.8444
2	591	0.7553		0.4342		1.0132	0.7806
3	592	0.6540		0.3548		0.7787	0.4077
4	591	0.5447		0.2571		0.8680	0.2193
Lowest Flow (%)	591	0.3782		0.1048		0.8208	0.5602
Highest - Lowest		0.5987	***	0.5120	***	0.2466	0.2842

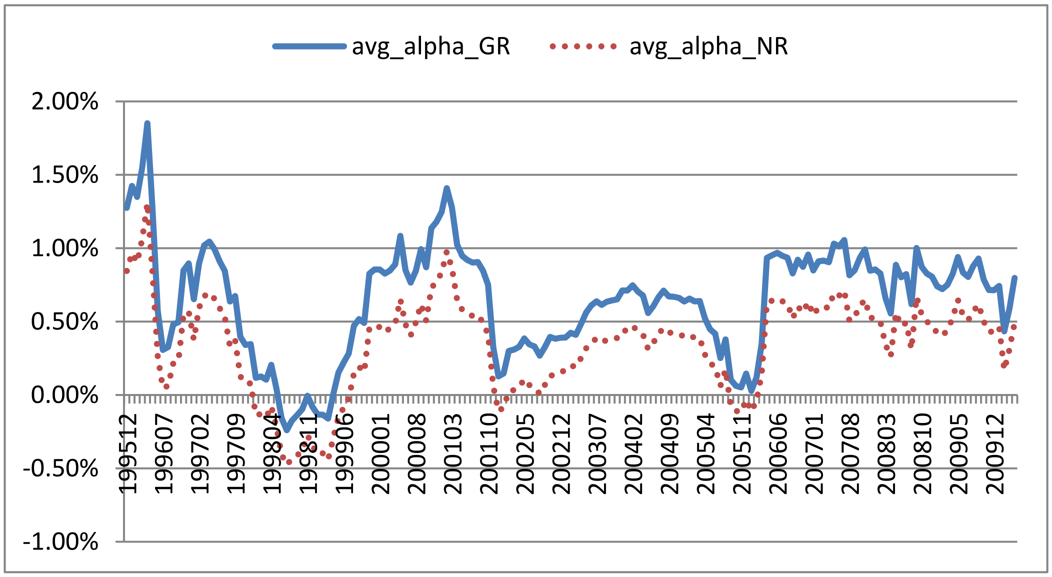

Figure 3.1. Average Alpha Over Time

APPENDIX

ALGORITHM FOR THE COMPUTATION OF DELTA, FEES, GROSS RETURNS AND FUND FLOWS

In this algorithm, we extend the algorithm of computation of delta as in Appendix A of Agarwal et al. (2009b) to allow accrual of incentive fees, monthly estimation, and inclusion of management fees. We calculate the monthly gross returns, gross asset values and fees of hedge fund, and the delta of manager's option, using net returns, net asset values and other hedge fund characteristic variables. It takes into account the high-water mark and hurdle rate provisions, as well as the monthly net flows of asset value.

As stated by Agarwal et al. (2009b), incentive fee contracts provide managers with options on investors' assets under management (AUM). Following Agarwal et al. (2009b), we define manager's option delta as the sensitivity of option value to a one percent change in asset value.

$$Manager'sOptionDelta = N(Z) \times S \times 0.01 \times IF\% \tag{A.1}$$

Z = $\frac{ln(S/X)+T(r+\sigma^2/2)}{\sigma\sqrt{T}}$,

S = spot price (market value of the investors assets as of end of current year)

X = exercise price (the market value of the investors assets that must be reached the subsequent year before incentive fees can be paid that year)

T = time to maturity of the option (1 year)

r = ln(1+ risk-free interest rate) (i.e., ln(1 + LIBOR rate for the subsequent year))

σ = volatility of monthly net returns (estimated over the year)

I = incentive fee rate (expressed as a fraction)

N( ) = cumulative distribution function (cdf) of standard normal distribution.

The managers option delta of the fund is the sum of the deltas from different sets of investors, each of whom has their own exercise price depending on when that individual entered the fund. To compute the spot price (S) and exercise price (X) used in the computation of delta above, we make the following assumptions:

The following assumptions are made to compute the gross return and fees.

1. Assets at inception are assumed to be that of the investor.

2. Investors' money flows occur at the end of each month.

3. When there is a net inflow, all the new flows come from a new investor. When there is a net outflow, we adopt first-in-first-out rule to decide which investor's money leaves the fund, and the accrued incentive fee for the outflow is paid to the manager.

4. Each investor has an individual exercise price depending on the timing of entering the fund, the hurdle rate and high-water mark provisions.

5. The high-water mark is the highest historical year-end NAV, or the initial per share price, whichever is higher. It is investor specific and reset at the end of each year. If there is also a hurdle rate provision, the high-water mark will grow at the hurdle rate each month.

6. Hurdle rate is the monthlirized three-month LIBOR (the London interbank offered rate) of US dollars for funds with a hurdle rate provision.

7. If no incentive fee is paid for a month due to insufficient returns, the hurdle for the next month is based on a geometrically compounded hurdle rate over that month.

8. Management fees are paid monthly.[1] Incentive fees are paid annually and accrued before the end of each year. The accrued incentive fees are reinvested in the fund before being paid to the managers, and the earnings from these investments belong to investors.

9. The manager reinvests all the previously-collected incentive fees into the fund after paying personal taxes. Offshore managers pay no personal taxes on incentive fees, whereas onshore managers pay a tax rate of 35%.

We adopt the following steps to calculate fees, gross returns, manager's investment and Delta.

1. The first investor enters the fund at the end of month 0, the second investor enters the fund at the end of month 1 if the net flow in the second month is positive, and so on.

2. The Gross Asset Value (GAV_t) per share of investor's investment is given by

$$
\begin{aligned}
GAV_t &= \frac{[NAV_{t-1} \cdot NShares_{t-1} + AIF_{t-1} \cdot \min(NShares_{t-2}, NShares_{t-1})]}{NShares_{t-1}} \\
&\quad \times (1 + GrossReturn_t) \qquad \text{(A.2)}
\end{aligned}
$$

3. Management fee of each investor is the a percentage ($MF\%_i$) of his net investment. The management fee per share is given by

$$MF_{i,t} = NAV_{t-1} \times MF\%_i \qquad \text{(A.3)}$$

[1] Agarwal et al. (2009b) assumed that monthly fees cover fixed costs. However, without imposing this assumption, we find that the management fee takes a significant portion of the total fees of hedge fund, thus may not be totally canceled out by fixed cost.

4. Calculate the accrued incentive fees of each investor. If there is a high-water mark provision, the accrued incentive fee of investor i in month t is given by

$$AIF_{i,t} = \max\{0, (GAV_t - MF_t - HWM_{i,t}) \times IF\%\} \tag{A.4}$$

   The accrued incentive fee of the fund is a weighted average of the accrued incentive fees of all current investors, with the weight equal to the number of shares each investor holds.

   If the fund has no high-water mark provision, then the incentive fee calculation of the investors is memoryless, and the per share monthly incentive fee and accrued incentive fee are given by

$$\begin{aligned} IF_{i,t} &= \max\{0, [GAV_t - MF_t - (NAV_{t-1} + AIF_{t-1}) \times (1 + hurdle_i \cdot H_t)]\} \\ &\quad \times IF\% \qquad \text{(A.5)} \\ AIF_{i,t} &= AIF_{i,t-1} + IF_{i,t} \qquad \text{(A.6)} \end{aligned}$$

5. At the end of each year, all shares with high-water mark lower than the year-end NAV will collapse into one series of shares with the high-water mark reset to the year-end NAV. Otherwise, the high-water mark of the investor remains unchanged.

6. Solve for the gross return numerically. The Gross Asset Value (GAV_t) is given by the following equation.

$$GAV_t = NAV_t + MF_t + AIF_t \tag{A.7}$$

   Substituting equation (A.2), (A.3) and (A.4) in equation (A.7), we can numerically solve for the gross return ($GrossReturn_t$).

7. Compute the net market value of investment of all investors, the number of shares, and fund flow of the month.

$$\begin{aligned} MVinv_t &= AUM_t - AIF_t \cdot NShares_{t-1} - MVmgr_{t-1} \\ &\quad \times (1 + GrossReturn_t) \qquad (A.8) \\ NShares_t &= MVinv_t \ / NAV_t \qquad (A.9) \\ Flow_t &= NAV_t \ (NShares_t - NShares_{t-1}) \qquad (A.10) \end{aligned}$$

8. Compute the market value of manager's investment. The market value of manager's investment in the fund, $MVmgr_t$, the sum of the month-end value of the manager's month beginning investment and the post-tax incentive fees earned in that month.

$$\begin{aligned} MVmgr_t &= MVmgr_{t-1}(1 + GrossReturn_t) \\ &+ \sum_i AIF_{i,t} \cdot \Delta NShares_{i,t} \cdot 1_{\Delta NShares_{i,t}<0} \cdot 1_{month \neq 12} \\ &+ AIF_t \cdot NShares_{t-1} \cdot 1_{month=12} \qquad (A.11) \end{aligned}$$

9. Calculate the exercise price X for each investor at the end of each year. The exercise price X_i is higher than the year-end high-water mark of investor i (if the fund has a high-water mark provision) or year-end NAV (if the fund lacks a high-water mark provision) by the hurdle rate (LIBOR if the fund has a hurdle rate provision, or 0 if the fund lacks a hurdle rate provision).

10. Using the S and X of various investors capital, compute the delta of each and sum them up along with the delta from the managers investment to estimate the total delta of the fund.

11. The *total delta* of the fund is the sum of delta from investors' assets (manager's option delta) and the delta from the manager's stake. Since all the return from

the manager's investment is retained, the delta from the manager's stake equals market value of manager's investment in the fund multiplied by 0.01 (i.e., when the fund earns one-percent return, the value of the manager's stake goes up by one percent). *Managerial ownership*, as we use in our analysis, is the market value of the manager's investment in the fund expressed as a fraction of the fund's total assets under management.

Table A.1. Definition of Factors

Factor	Description
MKTRF	Excess return of the CRSP value-weighted index
SMB	Fama-French size factor
HML	Fama-French value factor
SMBSQ	Fama-French size factor squared
HMLSQ	Fama-French value factor squared
D10YR	Change in the 10-year treasury yield
DSPRD	Change in the spread between BAA yield and 10-year treasury yield
PTFSBD	Primitive trend follower strategy bond
PTFSFX	Primitive trend follower strategy currency
PTFSCOM	Primitive trend follower strategy commodity
PTFSIR	Primitive trend follower strategy interest rate
PTFSSTK	Primitive trend follower strategy stock

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