Flows, Performance, and Managerial Incentives in Hedge Funds

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Abstract

Using a comprehensive database of hedge funds, we investigate two important issues. First, we examine the determinants of money-flows into hedge funds. In particular, we investigate how money-flows relate to past performance, managerial incentives, impediments to capital withdrawals, and past money-flows. Second, we analyze how future performance relates to fund size, past flows, managerial incentives, and impediments to withdrawals. For this purpose, we use a novel approach to model the incentive-fee contract of hedge fund managers as a portfolio of call options. In this framework, the delta of this option portfolio captures the managerial incentives.

We have several new and interesting findings. First, funds with good recent performance, higher delta, lower impediments to withdrawals, and greater past flows experience higher money-flows. Second, we find that larger funds with greater inflows are associated with poorer future performance, a result consistent with decreasing returns to scale. Also, funds with higher delta and greater impediments to capital withdrawals are associated with superior future performance. Overall, these results significantly improve our understanding of determinants of money-flows, nature of managerial incentives, behavior of investors, and drivers of performance in hedge funds.

Flows, Performance, and Managerial Incentives in Hedge Funds

In recent years, the hedge fund industry has emerged as an alternative investment vehicle to the traditional mutual fund industry. It differs from the mutual fund industry in several important ways. First, hedge funds are much less regulated than mutual funds and offer limited transparency and disclosure. Further, due to legal restrictions placed on advertising by hedge funds, information on them is harder to obtain. Second, hedge funds charge performance-based incentive fees (option-like contract), which help align the interests of manager and investors. Finally, hedge funds provide limited liquidity to investors compared to mutual funds as they often specify lockup periods and withdrawals are subject to notice and redemption periods.[1] These institutional differences have important implications for how investors allocate their money across different hedge funds as well as how money flows and incentives determine hedge fund performance in the future. This leads us to two important research questions. First, what are the determinants of money-flows in hedge funds? In particular, how do the money-flows relate to a fund's past performance (returns and persistence in returns), managerial incentives, and impediments to capital withdrawals (lockup and restriction periods)? Second, how does a fund's future performance relate to its size, money-flows, managerial incentives, and lockup and restriction periods?

Before elaborating these two research questions, it is important to understand the nature of managerial incentives in the hedge fund industry. Unlike most mutual fund managers, hedge fund managers are incentivized by option-like performance-based-fee contracts (Elton, Gruber,

[1] An investor has to wait for a few days after investing before he can withdraw his money (lockup period). After the lockup period is over, an investor wishing to withdraw still needs to give a few days advance notice ("notice period") and then has to wait for a few days more to receive his money back ("redemption period"). Hence, we add notice period and redemption period and for expositional convenience, call it as "restriction period".

and Blake, 2003).[2] Prior literature on hedge funds (Ackermann, McEnally, and Ravenscraft, 1999; Brown, Goetzmann, and Ibbotson, 1999; Liang, 1999; Edwards and Caglayan, 2001) has documented a positive relation between performance and incentive fee. This literature implicitly proxies managerial incentives by the percentage incentive fee charged by the hedge funds. However, this may be too simple a proxy because the incentive structures of hedge fund managers are much more complex. For example, the incentive fee, per se, does not take into account how far the fund is relative to its high-water mark. This is because two managers may be charging the same percentage incentive fee but one may be substantially below its high-water mark (i.e., the manager is underwater) while the other may be close to its high-water mark. Since the two managers face very different incentives, it is clear that the incentive fee has serious limitations in capturing the true incentives faced by a manager.[3]

We overcome these limitations by explicitly modeling the incentive-fee contract as a call option written by the investors on the assets under management, where the strike price is determined by the net asset value (NAV) at which different money-flows enter the fund, and the hurdle rate and high-water mark provisions. In general, capital invested at different points in time is subject to different high-water marks. Therefore, we model the incentive-fee-contract as a portfolio of call options with different strike prices. In this framework, the managerial incentives are captured through the delta of the manager's portfolio of call options. We define delta as the dollar increase in the incentive-fee-based compensation of the manager for an increase of one percent in the fund's return. The larger is the value of delta, the greater are the managerial

[2] Incentive fee contracts many a times include hurdle rate and high-water mark provisions. With a hurdle rate provision, the manager does not get paid any incentive fee if the fund returns are below the specified hurdle rate, which is usually a cash return like LIBOR. With a high-water provision, the manager earns incentive fees only on new profits, i.e., after recovering past losses, if any (see Goetzmann, Ingersoll and Ross (2003) for details).

[3] Ackermann, McEnally, and Ravenscraft (1999, pp. 860) acknowledge this limitation as follows: "The problem is that the relationship between high-water marks, incentive fees, and volatility is complicated. The relationship should depend on where the fund is relative to its high-water mark. This is further complicated by the fact that new investors may have different high-water marks than original investors."

incentives to deliver superior performance.[4] This is the first attempt in the hedge fund literature to properly quantify the incentives offered by the performance-based-compensation contracts of hedge fund managers and then use our measure of managerial incentives to examine how it relates to money-flows and future performance.

In addition to the contribution of explicitly measuring the managerial incentives, this paper makes two major contributions. The first one relates to the determinants of money-flows in hedge funds. As discussed, hedge funds differ from traditional asset management vehicles in several important ways. Therefore, one expects these differences to also influence the investors' hedge fund selection process. While we have a reasonable idea of the factors investors consider before placing their money in mutual funds (Ippolito, 1992; Chevalier and Ellison, 1997; Goetzmann and Peles, 1997; Sirri and Tufano, 1998), pension funds (Del Guercio and Tkac, 2002) and private equity funds (Kaplan and Schoar, 2003), we have limited understanding of the determinants of money-flows in hedge funds. Goetzmann, Ingersoll, and Ross (2003) (henceforth GIR) is the only paper to explore this issue for hedge funds by conducting a univariate analysis of money-flows and past returns. However, we believe that in addition to past returns, investors consider various other factors such as managerial incentives, lockup and restriction periods, and past flows. Therefore, we examine the determinants of money-flows in a multivariate setup that controls for these and other factors (like fund size, age, and volatility). Finally, in addition to these fund characteristics, investors may also pay attention to consistency in a fund's performance. Arguably, investors prefer to place their money in funds, which have performed consistently well. Therefore, we examine the relation between flows and persistence in past performance, an issue that has also not been hitherto explored.

[4] In our data, the correlation between delta and incentive fees is only 0.12.

The other major contribution of this paper relates to the role of fund size, past flows, managerial incentives, and impediments to capital withdrawal (lockup and restriction periods) in explaining the cross-sectional variation in fund performance. This is important because even if investors pay attention to past performance while making investment decisions, they particularly care about the fund's future performance. This issue gains even more importance in the context of markets in which hedge funds operate, where there may be capacity constraints and illiquidity problems. Therefore, fund size and large money-flows can adversely affect future performance. In addition, one expects the performance-based compensation (captured by the call-option-delta) to motivate the manager to deliver higher returns. Towards that end, we examine the relation between managerial incentives and future performance. Finally, features such as lockup and restriction periods enable managers to invest in illiquid securities and earn a liquidity risk premium. Therefore, we analyze how funds' future performance relates to lockup and restriction periods.

We have four new findings relating to flows, past performance, and managerial incentives. First, we find that money-flows chase recent good performance, a result different from that of GIR (2003), who find that the best performers experience outflows. In addition to the different methodologies in the two papers, we believe that the differences in regulatory and market environments during the two sample periods may also be responsible for the differences in the results (see Section III for more details). Interestingly, we find that the performance-flow relation is convex.[5] Second, we find that money-flows are significantly higher (lower) for funds that are persistent winners (losers). Third, we observe a positive relation between flows and delta after controlling for recent performance. This confirms that investors prefer to allocate capital to

[5] Our finding of a convex performance-flow relation is consistent with that of Chevalier and Ellison (1997), Goetzmann and Peles (1997), and Sirri and Tufano (1998) in the mutual fund industry.

funds where the manager has greater incentives to perform better. Since delta incorporates information about the entire history of returns and money-flows, this finding suggests that investors take into account entire history of returns and money-flows. Finally, we find that investors do not like impediments to capital withdrawals, as funds with longer lockup periods are generally associated with lower flows.

We have three new findings regarding a fund's future performance and its relation to its size, past flows, managerial incentives, and lockup and restriction periods. First, we find that both larger hedge funds as well as funds experiencing greater flows are associated with worse future performance (lower returns and lower probability of showing persistently good returns in the future). This finding is consistent with hedge funds facing decreasing returns to scale.[6] Second, we find greater managerial incentives are associated with better performance in the future. This justifies investors' preference for hedge funds with higher delta that we observe while examining the relation between flows and managerial incentives. Finally, we find that funds with greater impediments to capital withdrawals are associated with better performance in the future. This result is consistent with investors earning a liquidity risk premium.

The rest of the paper is organized as follows. Section I describes the data. Section II presents the testable hypotheses. Section III examines the role of past performance, managerial incentives, and impediments to capital withdrawals on new money-flows. Section IV investigates the role of fund size, money-flows, managerial incentives, and impediments to capital withdrawals on the cross-sectional variation in future fund performance. Section V offers concluding remarks with suggestions for future research.

[6] It is also consistent with the underlying assumption of decreasing returns to scale in Berk and Green (2002). Chen, Hong, Huang, and Kubik (2002) find similar evidence in the mutual fund industry.

I. Data

A. Data Description

In this paper, we construct a comprehensive hedge fund database that is a union of three large databases, namely HFR, TASS, and ZCM/MAR.[7] This database has monthly net-of-fee returns, monthly assets under management, and other fund characteristics such as lockup and restriction periods, management and incentive fees, inception date, and fund strategy. This enables us to resolve occasional discrepancies among different databases as well as create a sample that is more representative of the entire hedge fund industry. Our sample period extends from January 1994 to December 2000. We focus on this period for three reasons. First, the number of funds prior to our sample period is relatively few. Second, the databases do not extensively cover "dead" funds before 1994.[8] Finally, publicly disseminated data on hedge fund indices has only been available since 1994, which enabled investors to assess the relative performance of a fund more easily. Therefore, we conduct our analysis using 1994-2000 data.

In Table I (Panel A), we provide the breakdown of funds from different data vendors. After merging the three databases, we find that there are 1776 live and 1655 dead hedge funds.[9] In Figure 1, we report the overlap between the three databases with a Venn diagram. There is an overlap of 30% in the number of hedge funds across the three databases, with HFR having the largest coverage (54%). It also highlights that there are a large number of hedge funds that are

[7] In the past, researchers have used one or more of the three major hedge fund databases. For example, Fung and Hsieh (1997) use TASS database, Ackermann, McEnally, and Ravenscraft (1999) use HFR and ZCM/MAR databases, Agarwal and Naik (2000, 2004) and Liang (2000) uses HFR and TASS databases, while Brown, Goetzmann, and Park (2001) use data from Offshore Funds Directory and TASS.
[8] It is important to note that the word "dead" is misleading and "missing-in-action" may be a more appropriate term as they include funds that are liquidated, merged/restructured, and funds that stopped reporting returns to the database vendors but may have continued operations. However, in order to be consistent with previous research, we continue to call them "dead" funds.
[9] We exclude managed futures, natural resources, mutual funds, and 'other' hedge funds since these categories are not usually considered as "typical" hedge funds. We also exclude long-only funds, Regulation D funds, and funds with missing strategy information.

unique to each of the three databases and thus, merging them helps in capturing a more representative sample of the hedge fund universe.

Even though hedge funds market themselves as “absolute performers”, investors arguably evaluate the performance of a hedge fund relative to its peers. Unfortunately, there is no universally acceptable way of classifying hedge funds into different styles. Academic research (Fung and Hsieh, 1997; Brown and Goetzmann, 2003) shows that there are few distinct style factors in hedge fund returns. Following these insights, we classify the reported hedge fund strategies into four broad categories: Directional, Relative Value, Security Selection, and Multi-Process Traders. In Appendix A, we describe the mapping between the data vendors' classification and our classification. In Panel B of Table I, we report the distribution of hedge funds across the four broad strategies. We present in Table II, the means and standard deviations of monthly net-of-fee returns, volatility of returns, lockup and restriction periods, age, management and incentive fees for hedge funds. The average management fee and incentive fee are 1.22% and 18.24% respectively. The average lockup and restriction period across the funds that impose these impediments to capital withdrawals are 0.98 year and 0.19 year respectively.

B. Computation of Money-Flows

We first compute dollar flows for fund *i* during month *m* as follows

$$Dollar\ Flow_{i,m} = AUM_{i,m} - AUM_{i,m-1}\left(1 + Return_{i,m}\right) \quad \textbf{(1)}$$

where, $AUM_{i,m}$ and $AUM_{i,m-1}$ are the size for fund *i* at the end of month *m* and month *m-1* and $Return_{i,m}$ is the return for fund *i* during month *m*.[10] We aggregate the monthly flows during

[10] This formula assumes that the fund flows occur at the end of the month. For the sake of robustness, we also compute money-flows assuming that they occur at the beginning of the month and find very similar results. When AUM data is not available at a monthly frequency, we compute flows for coarser intervals.

the year t to estimate annual flows (*Annual Dollar Flow*$_{i,t}$). As in Chevalier and Ellison (1997) and Sirri and Tufano (1998), we scale annual dollar flows by beginning-of-year assets under management to capture the change in size due to net money-flows.

$$Flow_{i,t} = \frac{Annual\ Dollar\ Flow_{i,t}}{AUM_{i,t-1}} \quad \textbf{(2)}$$

In Table III, we report the trend in assets under management (AUM) and money-flows in the hedge fund industry. As can be seen from Table III, the total assets under management for hedge funds have grown five-fold from $40 billion in December 1993 to $201 billion in December 2000. We observe that, in general, more than 25% of funds experience outflows. Further, the mean flows are systematically higher than the median flows suggesting that some funds experienced significant growth in the assets under their management.

C. Computation of Managerial Incentives

As described in the introduction, incentive fee contract amounts to the investor having written a fraction of a call option on the assets under management. For example, if incentive fee equals 20 percent, then it is equivalent to the investor having written 0.2 of a call option on the money invested. When money gets invested in a fund at different points in time, each investment is associated with its own high-water mark, which gets revised upwards for future years if the fund delivers positive returns. In addition, when a hurdle rate is specified, the manager needs to exceed it before he can claim an incentive fee. Therefore, incentive-fee contracts endow the manager with a portfolio of call options. The value of each of the call options depends on the NAV at which the money came in, its high-water mark, and hurdle rate.

The option-like compensation provides the fund manager with incentives to deliver superior returns.[11] We proxy these incentives by the delta of the portfolio of call options, which equals the dollar change in the incentive fee for a one percent change in the fund's return. The greater the delta, the larger is the incentive to deliver superior returns. We describe the procedure of computing delta in Appendix B.

By definition, delta depends on the degree of moneyness of the portfolio of options generated by money-flows over time, which in turn, depends on whether a fund has had a negative return in a year or in previous years. Clearly, if the fund has a negative return during a year, it will be below its high-water mark. However, a fund with a positive return in a given year could still be below its high-water mark if its cumulative negative returns in prior years exceed the positive return in the current year.

We report the summary statistics of funds with negative returns and those below high-water mark in Panel B of Table III. We find that the percentage of funds with negative returns has increased from 8.4% to 33.1% from December 1993 to December 2000. The mean (median) loss has also increased from 11.2% (7.9%) to 19.9% (15.0%) over this period. Consistent with our discussion above, a larger proportion of funds are below their high-water mark (50.2% and 51.3% in December 1993 and December 2000 respectively). The shortfall below high-water mark for these funds will however be smaller than the magnitude of loss in that year because it includes funds that have positive returns during that year and are below high-water mark due to poor return history. As expected, the mean (median) shortfall below high-water mark varies from 2.9% (0.3%) in December 1993 to 8.3% (1.2%) in December 2000.

[11] It is important to note that option-like payoffs also influence risk-taking incentives of hedge fund managers. Agarwal, Daniel, and Naik (2003) examine these and find that fund volatility is positively related to both implicit and explicit risk-taking incentives.

Finally, we report the summary statistics of delta in Panel C of Table III.[12] Over the sample period, we find that mean (median) delta across all hedge funds has increased from $130,000 ($30,000) in December 1993 to $240,000 ($50,000) in December 2000.[13]

Having described the data, we now present our set of testable hypotheses for this study.

II. Testable Hypotheses

We develop four hypotheses with respect to the determinants of money flows and three hypotheses regarding the determinants of the cross-sectional variation in fund performance.

Due to lack of disclosure and transparency, hedge fund investors need to rely more on past performance. Further, there is limited information (usually only past performance figures) available for hedge funds as they are restricted from advertising. This suggests that investors may infer a manager's ability through past performance (returns and persistence in returns), and invest in funds with better performance, which translates into the following hypothesis.

Hypothesis 1: Funds with better past performance should be associated with higher flows

As discussed before, performance-based compensation of hedge fund managers provides strong incentives to the manager to perform better. This implies that managers whose funds are near or at their high-water marks face better incentives compared to those that are substantially below their high-water marks. Investors are likely to take this into account and allocate capital to managers facing better incentives. Therefore, we expect to see a positive relation between flows and our measure of managerial incentives, delta, leading us to the following hypothesis.

[12] We measure delta in millions of dollars. However, it is simple to convert our dollar delta into the standard Black and Scholes (1973) call option delta by dividing our dollar delta by (0.01*incentive fee*investors' assets).

[13] Like hedge fund managers, top executives of corporations receive option-like payoffs, which create similar managerial incentives. It is interesting to compare the level of managerial incentives in these two industries. Coles, Daniel, and Naveen (2003) report the mean (median) delta of executive stock options for the top 1500 firms in S&P during 1992-2000 to be $584,000 ($196,000). See Murphy (1999) and Core, Guay, and Larcker (2003) for a survey of literature on executive compensation.

Hypothesis 2: Funds with higher managerial incentives (delta) should experience higher flows

Hedge funds are characterized by lockup and restriction periods suggesting significant illiquidity for its investors. All else equal, one would expect investors to prefer more liquid funds implying a negative relation between flows and impediments to capital withdrawals (lockup and restriction periods), leading us to the following hypothesis.

Hypothesis 3: Funds with longer lockup and restriction periods should be associated with lower flows

In addition to past performance, managerial incentives, and illiquidity, investors may also pay attention to past flows while selecting hedge funds. There are two possible explanations. Higher flows could signal *other* investors' confidence in the ability of its manager. Further, past flows may proxy for non-performance variables such as reputation and marketing efforts that can influence investors' decisions. This leads us to the following hypothesis.

Hypothesis 4: Funds with higher past flows should attract higher current flows

Hedge funds often employ trading strategies to exploit quasi-arbitrage opportunities in financial markets. Hence, there is only limited capital that can be usually employed in some of these strategies. For example, merger arbitrage funds take bets on firms engaged in mergers and acquisitions (M&A). Clearly, the amount of money that they can invest in such trading is restricted by the size of the M&A market. This implies that funds with large money-flows and/or larger size may find it difficult to continue delivering high returns if they are unable to deploy their entire capital into their trading strategies. In addition, such funds also are subject to significant execution costs (including market-impact costs, implementation shortfall, etc.), which can further hurt their performance. Finally, Chen, Hong, Huang, and Kubik (2002) document that fund size erodes performance in the mutual fund industry due to liquidity and organizational diseconomies. Overall, these factors suggest that higher money-flows into funds with larger size may hinder their future performance due to decreasing returns to scale. This leads us to the fifth hypothesis.

Hypothesis 5: Hedge funds with larger size and higher flows should be associated with worse future performance

As stated in Hypothesis 2, performance-based compensation in hedge funds is designed to motivate the manager to perform better in the future. Clearly, manager of a fund with larger delta enjoys higher increase in wealth per unit of fund return compared to the one with smaller delta. This leads us to the following hypothesis.

Hypothesis 6: Funds with greater managerial incentives (delta) should be associated with better future performance

Finally, hedge funds specifying longer lockup period may be able to invest in illiquid securities. Similarly, longer restriction periods provide the manager more flexibility in unwinding his positions in the illiquid securities. Together these two should help the fund earn higher return by capturing liquidity risk premium. This leads us to the last hypothesis.

Hypothesis 7: Hedge funds with longer lockup and restriction periods should be associated with better performance

We test these seven hypotheses in the Sections III and IV of the paper.

III. Determinants of Money-Flows

In this section, we investigate the determinants of money-flows into hedge funds. It may be that investors follow a top-down approach where they first choose the broad strategies in which to invest, and then decide in which funds to invest. Barberis and Shleifer (2003) argue that investors first group assets into categories to allocate money at the category level instead of the individual asset level. Therefore, we first explore the performance-flow relation at a strategy level. For this purpose, we sum up annual dollar flows across all funds within a strategy and obtain aggregate strategy-level flows. For each strategy, we plot in Figure 2 the annual dollar flows of all the funds within that strategy against their prior-year's weighted average returns. We use both equally-weighted and value-weighted (weighted by AUM) returns at the strategy level. Figure 2 suggests that, in general, money-flows chase recent performance for all four strategies as well as for all the funds considered together.[14] We investigate this finding further at the fund level using our composite database.

A. Performance, Delta, Impediments to Withdrawals, and Money-flows

To examine the performance-flow relation, we need to assess performance. While it would be useful to estimate risk-adjusted performance, this is a perilous task given the non-normality in hedge funds returns and option-like dynamic trading strategies adopted by hedge funds (Fung and Hsieh, 1997, 2001; Goetzmann et al., 2002; Agarwal and Naik, 2004). To the extent that funds following a particular strategy face similar risks, we follow Brown, Goetzmann, and Ibbotson (1999) and Agarwal and Naik (2000) and use returns relative to one's peer group as a measure of performance.

In order to compare our findings for hedge funds, with those of Sirri and Tufano (1998) for mutual funds, we follow a similar methodology. We classify each fund-year observation into one of five quintiles based on performance. On a univariate basis, we find that the average inflow into funds in the top (first) quintile is 63% compared to an average outflow of 3% for funds in the bottom (fifth) quintile. Arguably, investors consider factors in addition to performance, such as managerial incentives, lockup and restriction periods, and past flows while making their

[14] Getmansky (2003) examines the competition for flows at the strategy level and its effect on funds' survival.

investment decisions. They may also pay attention to size, volatility, age, etc. Therefore, we examine the determinants of money-flows into hedge funds by estimating the following multivariate regression:

$$\begin{aligned} Flow_{i,t} &= \beta_0 + \sum_{j=1}^{5} \beta_1^j \left(Qrank_{i,t-1}^j\right) + \beta_2 Delta_{i,t-1} + \beta_3 Lockup_i + \beta_4 Restrict_i + \beta_5 Flow_{i,t-1} \\ &\quad + \beta_6 Size_{i,t-1} + \beta_7 \sigma_{i,t-1} + \beta_8 I\left(YoungFund_{i,t-1}\right) + \beta_9 I\left(OldFund_{i,t-1}\right) + \beta_{10} MFee_i \\ &\quad + \beta_{11} Return_{i,t} + \sum_{s=1}^{3} \beta_{12}^s I(Strategy_{i,s}) + \varepsilon_{i,t} \end{aligned} \qquad \textbf{(3)}$$

where, $Flow_{i,t}$ and $Flow_{i,t-1}$ are the money-flows in fund *i* in years *t* and *t-1*, $Qrank_{i,t-1}^j$ is the fractional rank of fund *i* in quintile *j* for year *t-1*, $Delta_{i,t-1}$ is the natural logarithm of delta of the managers' incentive-fee-contract for fund *i* as of end of year *t-1*,[15] $Lockup_i$ and $Restrict_i$ are the lockup and restriction periods (in years) for fund *i*, $Size_{i,t-1}$ is the size of the fund measured as the natural logarithm of the AUM for fund *i* at time *t-1*, $\sigma_{i,t-1}$ is the standard deviation of the monthly returns of fund *i* during year *t-1*, $I\left(YoungFund_{i,t-1}\right)$ is an indicator variable for younger funds that takes the value 1 if the fund age is in the bottom one-third of funds at the end of year *t-1*, $I\left(OldFund_{i,t-1}\right)$ is an indicator variable for older funds that takes the value 1 if the fund age is in the top one-third of funds at the end of year *t-1*, $MFee_i$ is the management fees charged by fund *i*, $Return_{i,t}$ is the return of fund *i* in year *t*, $I\left(Strategy_{i,s}\right)$ are strategy dummies that take the value 1 if fund *i* belongs to strategy *s*, and $\varepsilon_{i,t}$ is the error term.[16]

We construct the fractional rank quintiles, $Qrank_{i,t-1}^j$, where *j* = 1, 2, 3, 4, and 5 as per Sirri and Tufano (1998). First, each fund *i* is given a fractional rank, $Frank_{i,t-1}$, from 0 through 1 based

[15] We measure delta in millions of dollars and take its natural logarithm to mitigate the outlier effect.
[16] We winsorize top 1% of the explanatory variables in order to minimize the influence of outliers.

on returns in year *t-1*. This fractional rank represents its fractile performance relative to other funds in the same period. For example, if $Frank_{i,t-1}$ is 0.35, it implies that the fund was better than 35% of its peer group. We estimate the coefficients on fractional ranks using piecewise linear regression framework over five quintiles. Towards that end, we define $Qrank^{5}_{i,t-1}$ for fund *i* in year *t-1*, the bottom quintile rank, to equal Min (0.2, $Frank_{i,t-1}$), $Qrank^{4}_{i,t-1}$ = Min (0.2, *Frank*- $Qrank^{5}_{i,t-1}$), $Qrank^{3}_{i,t-1}$ = Min (0.2, $Frank_{i,t-1}$- $Qrank^{4}_{i,t-1}$ - $Qrank^{5}_{i,t-1}$) and so forth up to the highest performance quintile, $Qrank^{1}_{i,t-1}$, i.e., the top quintile. For example, if a fund's fractional rank is 0.35, it would have $Qrank^{5}$ = Min (0.2, 0.35) = 0.2, and $Qrank^{4}$ = Min (0.2, 0.35-0.2) = 0.15, $Qrank^{3}$ = Min (0.2, 0.35-0.2-0.15) = 0, and similarly higher quintile ranks, $Qrank^{2}$ and $Qrank^{1}$, will also be zero. Clearly this specification captures the *incremental* slope coefficient with respect to the previous performance quintile. In this specification, convexity in performance-flow relationship manifests itself in the form of a slope coefficient of a given quintile being significantly higher than that of the previous quintile.

The multivariate specification in equation (3) can be estimated either using pooled regression method or using Fama and MacBeth (1973) procedure. Sirri and Tufano (1998) highlight the potential problems in using pooled regression technique, which implicitly assumes each fund-year observation to be an independent observation. If this assumption is violated, it may result in underestimation of standard errors. Therefore, Sirri and Tufano (1998) recommend the use of Fama and MacBeth (1973) procedure that incorporates potential non-independence of each fund-year observation and produces more conservative estimates of the significance levels. We report the results of regression based on Fama-MacBeth (1973) procedure in Table IV. For the sake of robustness, we repeat our analysis using pooled regressions and obtain similar results (not reported for the sake of brevity).

The results in Model 1 show that only the coefficients on the top and the third quintile are significantly positive at the 1% level. The insignificant coefficients on the bottom two quintiles imply that the flows into the bottom 40% of the funds are not significantly different from zero. In contrast, the significant coefficient on the third quintile (coeff.=1.494) implies that the funds in this quintile attract 1.5% more flows (than those for the funds at the 40th percentile) for every 1 percentile improvement in performance. Again, the fourth quintile being insignificant means that the funds lying between the 60th and 80th percentile obtain flows similar to the funds at the 60th percentile. Finally, the significant coefficient on the top quintile (coeff.=1.798) implies that funds in this quintile get 1.8% more flows (than those for the funds at the 80th percentile) for every 1 percentile improvement in performance. These findings confirm Hypothesis 1 that well-performing funds attract significantly higher flows compared to poorly performing ones.

Sirri and Tufano (1998) document a convex performance-flow relation for mutual funds by conducting a Chow test on a pairwise basis on the coefficients on adjacent performance quintiles. We examine if similar convexity exists for hedge funds and find the slope coefficient on the third quintile is significantly greater than that on the fourth quintile (p value = 0.04). This suggests a convex performance-flow relation with the kink occurring at the 40th percentile as compared to the 80th percentile in case of mutual funds.[17]

Next, as in Sirri and Tufano (1998), we investigate the possibility that investors might consider coarser performance groups by combining the middle three quintiles into one group.

[17] Chevalier and Ellison (1997) document that money-flows of older funds are less sensitive to recent returns. We examine this for hedge funds by interacting the five performance quintiles with our two age dummies and estimate the regression in equation (3) after including these interaction terms (results not reported). Chow test indicates three kinks (at the 40th, 60th, and 80th percentiles) for younger funds but not for the older funds. This suggests that similar to mutual fund industry, flows into the younger funds are more sensitive to recent performance.

The results in Model 2 of Table IV show that the coefficient of the top quintile (coeff.=1.509) and the middle three quintiles pooled together (coeff.=0.747) are significantly positive at the 5% and 1% level respectively, while the bottom quintile coefficient is indistinguishable from zero. These results once again lend strong support to Hypothesis 1 and confirm that the well-performing funds attract significantly greater flows than the poorly performing ones.

Hypothesis 2 suggests that funds with better managerial incentives (greater delta) should attract higher flows. The positive and significant slope coefficient for delta in Models 1 and 2 (coeff.=0.011) is consistent with this hypothesis.[18] Further, the impact of delta is also economically significant. An increase in the delta from 25th percentile ($10,000) to 75th percentile ($131,000) is associated with an increase in annual flows by 2.8% compared to the median flow of 11.7%. This suggests that investors prefer to invest in funds whose managers' interests are better aligned with theirs.

Hypothesis 3 suggests that funds with lower liquidity (longer lockup and restriction periods) should attract lower flows. The slope coefficients on lockup period in Models 1 and 2 are negative and significant at the 5% level while those on restriction period are indistinguishable from zero. Further, in terms of economic significance, the slope coefficients on lockup period of -0.091 and -0.087 imply that an increase of one year in the lockup period is associated with about 9% lower flows. Overall, this finding lends support to Hypothesis 3.

Hypothesis 4 suggests that funds with higher past flows should attract higher current flows. The slope coefficients on past flows in Models 1 and 2 are positive (coeffs.=0.052 and 0.053) and significant at the 1% level. Further, the relation between past and current flows is also economically significant. An increase in past flows from 25th percentile (-18%) to 75th percentile

[18] For robustness, we examine if there is non-linear relation between flows and delta by including square of delta in equation (3) and find the coefficient on the squared term to be positive but not significant.

(39%) is associated with an increase in annual flows by 3.0%. Overall, this finding supports our prediction in Hypothesis 4.[19]

In summary, we find that flows are positively related to past performance, managerial incentives, and past flows while they are negatively related to lockup period. Overall, these findings lend support to our first four hypotheses.

B. Robustness checks

In this subsection, we examine the robustness of the above findings to account for funds that have been liquidated and funds that are closed for new investment. We also examine the robustness of our results to contemporaneous returns and existence of spillover effects.

B.1 Accounting for liquidated funds

For our performance-flow regression in equation (3), we need data on annual flows. However, if a fund disappears from our database during a year, it will not have annual flows in the year of its disappearance. Unlike mutual funds, where liquidation due to poor performance is the only reason for fund's disappearance, hedge funds may disappear for other reasons as well. These reasons include delisting by the data vendor, non-reporting by fund, change in fund names, and mergers (Fung and Hsieh, 2000). Goetzmann and Peles (1997) assign a flow of -100 percent in the last year for those funds that disappear due to poor performance. Following their insights, we examine the robustness of our results by assigning a flow of -100 percent in the last year for funds that disappear due to liquidation. We continue to find a convex performance-flow relation. This confirms that our results are not sensitive to exclusion of last year's flows for liquidated funds.

[19] Our results are robust to replacing Younger Fund and Older Fund dummies by a continuous variable for Age.

B.2 Accounting for funds that are closed for new investment

Some of the well-performing hedge funds may be closed for new investment. For these funds, one would not expect to find significant money inflows despite their good performance. Presence of such funds in our sample should bias *against* finding a significant performance-flow relation. In other words, if one were to estimate the performance-flow relation only for the funds that are open to investment, one should find a stronger performance-flow relation. We test this conjecture by estimating the performance-flow relation by selecting funds that are open to investment and compare the findings with those obtained when all funds are included. Since, "open to investment" variable is only available for the year in which the data is purchased, (i.e., year 2000 in our case), we estimate the regression in equation (3) for year 2000. When we consider all funds, we find the slope coefficients on the third and top quintile to be significant (coeffs.=2.836 and 2.661). In contrast, when we consider only funds that are open to investment, we find that these slope coefficients are significant and higher in magnitude (coeffs.=3.997 and 3.467). These results confirm that including funds that are closed for new investment can only bias against finding strong performance-flow relation.

B.3 Exclusion of Contemporaneous Performance (Returns)

We include returns at time t ($Return_t$) in equation (3) to be consistent with Chevalier and Ellison (1997). One may argue that contemporaneous returns may not be in the information set of investors. Hence, for robustness, we repeat our analysis by excluding this variable from equation (3) and find that our results remain unchanged.

B.4 Are there any spillover effects in hedge funds?

Recent research in mutual funds suggest that there are significant spillover effects, that is "star" or well-performing funds within a fund family can lead to an increase in the flows to other funds in that family (Khorana and Servaes, 2000; Massa, 2000; Ivkovich, 2001; Nanda, Wang, and Zheng, 2002). We examine if there are similar spillover effects in the hedge fund industry. Unlike mutual funds, multiple-fund families are uncommon in hedge funds. The average number of funds per family across our sample period is 1.3 (minimum of 1 fund and a maximum of 11 funds per family) with about 80% of the funds not belonging to a family. In order to examine spillover effects, we include performance of other funds in a family as an additional explanatory variable in equation (3). In unreported results, we find the slope coefficient on this variable to be positive but not significant.

C. Comparison of results with Goetzmann, Ingersoll and Ross (2003)

Although our finding of a convex performance-flow relation is consistent with those of Chevalier and Ellison (1997) and Sirri and Tufano (1998) for mutual funds, they differ from those of GIR (2003). In addition to the differences in the methodologies of the two papers, we believe that the differences in the regulatory or market environments during the periods covered in the two studies are responsible for the differences in the findings. For example, during our sample period, the restriction on the maximum number of qualified investors was relaxed. Further, data on hedge funds as well as a range of hedge fund indexes started becoming widely available. These changes made it easier for investors to obtain information about hedge funds and to compare their performance with peer group. To examine if the differences in the results are indeed attributable to the changing nature of the industry, we repeat our analysis, as in GIR, using only offshore funds from our sample during 1989-1995. It is important to note that the two samples are not identical as GIR use Offshore Funds directory while we use offshore funds included in the our composite database created by merging HFR, TASS, and ZCM/MAR databases. Instead of GIR's finding of outflows for top performers, we find that the top performers experience flows that are indistinguishable from zero (see Appendix C).

D. Alternative measure of past performance: Persistence in returns

In above subsections A, B, and C, we considered last year's returns as our measure of performance. A stronger signal of manager's ability is persistence in performance and not simply one year of superior performance. Investors should therefore direct more flows to managers who show persistence. Therefore, in this subsection, we examine the relation between money-flows and persistence in prior performance. To capture persistence, we follow Brown, Goetzmann, and Ibbotson (1999) and Agarwal and Naik (2000) and define a fund to be a winner (loser) in year *t*, if its returns are greater (lesser) than the return of the median fund in its peer group in that year. The indicator variable $I(Persistent\ Winner_{i,t-1})$ equals 1 if fund *i* is a winner in years *t-1* and *t-2*, and equals 0 otherwise. Similarly, the indicator variable $I(Persistent\ Loser_{i,t-1})$ equals 1 if fund *i* is a loser in years *t-1* and *t-2*, and equals 0 otherwise.

We investigate the persistence-flow relation by estimating the following regression:

$$\begin{aligned} Flow_{i,t} = \gamma_0 + \gamma_1 I\left(Persistent\,Winner_{i,t-1}\right) + \gamma_2 I\left(Persistent\ Loser_{i,t-1}\right) + \gamma_3 Delta_{i,t-1} \\ + \gamma_4 Lockup_i + \gamma_5 Restrict_i + \gamma_6 Flow_{i,t-1} + \gamma_7 Size_{i,t-1} + \gamma_8 \sigma_{i,t-1} + \gamma_9 I\left(YoungFund_{i,t-1}\right) \\ + \gamma_{10} I\left(OldFund_{i,t-1}\right) + \gamma_{11} MFee_i + \gamma_{12} Return_{i,t} + \sum_{s=1}^{3} \gamma_{13}^{s} I(Strategy_{i,s}) + e_{i,t} \end{aligned} \quad \textbf{(4)}$$

We report the results from regression in equation (4) in Table V. Since, we have both Persistent Winner and Persistent Loser indicator variables in the regression, the excluded category of funds is the one that shows reversals, i.e., funds that are winner in one year and loser in the other.

We find that the coefficient of Persistent Winner is significantly positive (coeff.=0.205) for hedge funds implying that the flow is 20.5% higher for funds which exhibit persistently good returns compared to those that exhibit reversals. Similarly, the coefficient of Persistent Loser is significantly negative (coeff.=-0.141) for hedge funds. This implies that consistently poorly performing funds experience 14.1% lower flows compared to those exhibiting reversals. These results suggest that money-flows are higher for funds with better past performance. These numbers are also economically significant given that the median flow is 11%. Further, slope coefficient on delta is significantly positive (coeff.=0.013) suggesting that funds with better managerial incentives attract higher flows. As expected, the slope coefficients on lockup and restriction periods are negative, although not significant. Finally, the slope coefficient on past flows is positive (coeff.=0.150) and significant at the 5% level. This suggests that funds with higher past flows are associated with higher current flows. Overall, these results lend support to hypotheses 1, 2, and 4.[20]

Having tested our first four hypotheses relating to determinants of money-flows in hedge funds, in the next section, we test the remaining three hypotheses regarding how future performance relates to fund size, past flows, managerial incentives, and impediments to capital withdrawals.

IV. Relation between fund size, past flows, managerial incentives, lockup and restriction periods, and future performance

[20] In order to examine if persistence matters over and above last year's returns, one can include last year's returns along with persistence dummies in equation (4). However, as these two are highly correlated, we included the residuals of regression of last year's returns on persistence dummies as an additional variable and find it to be significant. The coefficients on Persistent Winner and Persistent Loser dummies continue to be significant, confirming that investors care about persistence in addition to the last year's returns.

In this section, we test hypotheses 5, 6, and 7 by examining how future performance relates to fund size, past flows, managerial incentives, and lockup and restriction periods. Towards that end, we estimate the following regression:

$$Return_{i,t} = \lambda_0 + \lambda_1 Size_{i,t-1} + \lambda_2 Flow_{i,t-1} + \lambda_3 Delta_{i,t-1} + \lambda_4 Lockup_i + \lambda_5 Restrict_i + \lambda_6 \sigma_{i,t-1} + \lambda_7 I\left(YoungFund_{i,t-1}\right) + \lambda_8 I\left(OldFund_{i,t-1}\right) + \lambda_9 MFee_i + \sum_{s=1}^{3} \lambda_{10}^{s} I(Strategy_{i,s}) + \xi_{i,t} \quad \textbf{(5)}$$

We report our findings in Table VI. The results of Model 1 show that the slope coefficient on size is negative (coeff.=-0.012) and significant suggesting that larger funds are associated with lower returns in the following year. The slope coefficient on flow is also negative (coeff.=-0.007) and significant indicating that funds with greater flows are associated with worse returns in the subsequent year. In terms of economic significance, an increase in the size from 25th to 75th percentile is associated with a return decrease of 2.6% in the following year, compared to the median annual return of 12.4%. A similar increase in flow from the 25th to 75th percentile is associated with a return decrease of 0.6%. This suggests that compared to flow, size has a bigger impact on the future hedge fund returns. Overall, these results suggest that funds with larger size and greater flows are associated with worse returns in the future. This finding lends strong support to Hypothesis 5.

When we examine the relation between managerial incentives and future performance, we find that the slope coefficient on delta is positive (coeff.=0.005) and significant, implying that higher delta is associated with higher returns in the following year. The impact of delta is economically significant. An increase in the delta from 25th percentile ($10,000) to 75th percentile ($131,000) is associated with a return increase of 1.2% compared to the median annual return of 12.4%. Funds with greater managerial incentives are associated with better future performance as we predict in Hypothesis 6.

Finally, we find the slope coefficient on lockup period to be positive (coeff.=0.040) and significant. This result is also economically significant. An increase of one year in the lockup period is associated with 4% increase in returns.[21] The coefficient on restriction period is positive (coeff.=0.118) although not significant. These findings indicate that funds with substantial impediments to capital withdrawals are associated with better performance. This lends support to our Hypothesis 7.

Since hedge funds invest in relatively illiquid securities, it can potentially induce serial correlation in monthly returns (Getmansky, Lo, and Makarov, 2003). We believe this should not affect our analysis, which uses annual returns. However, for robustness, we include lagged annual returns as an additional control variable in equation (5). We find that the slope coefficient on lagged returns variable is not significant and our results (not reported) remain unchanged.

A. Logistic specification

To allow for the possibility that the relation between fund size, past flows, managerial incentives, lockup and restriction periods, and future performance may be non-linear, we adopt a logistic regression approach. The dependent variable here is WINNER, which takes the value 1 if a fund has above-median annual returns in its peer group.[22] Towards that end, we estimate the following logistic regression:

$$\begin{aligned} WINNER_{i,t} &= \phi_0 + \phi_1 Size_{i,t-1} + \phi_2 Flow_{i,t-1} + \phi_3 Delta_{i,t-1} + \phi_4 Lockup_i + \phi_5 Restrict_i + \phi_6 \sigma_{i,t-1} \\ &+ \phi_7 I\left(YoungFund_{i,t-1}\right) + \phi_8 I\left(OldFund_{i,t-1}\right) + \phi_9 MFee_i + \sum_{s=1}^{3} \phi_{10}^{s} I(Strategy_{i,s}) + \zeta_{i,t} \end{aligned} \qquad \textbf{(6)}$$

[21] See Aragon (2003), who compares hedge funds with and without lockups and documents existence of liquidity premium.
[22] For robustness, we also define a fund as a winner if its returns fall in the top quartile of its peer group and find our results to be qualitatively similar.

We report the results from this regression in Model 2 of Table VI. The results show that the slope coefficients on both size and flow are significantly negative (coeffs.=-0.107 and -0.044 respectively). We find that an increase in size from the 25^{th} to 75^{th} percentile is associated with a decrease in the probability of being a winner by 5.5% (unconditional probability of being a Winner = 50%). In contrast, increase in flows from the 25^{th} to 75^{th} percentile is associated with a decrease in the probability of being a winner by 0.9%. As in the case of OLS results, these findings suggest that size has a bigger impact on hedge fund's future performance compared to flows. Overall, these results lend further confirmation to Hypothesis 5 that funds with larger size and greater flows are associated with worse performance, i.e., lower likelihood of being a winner in the future.

As in case of the OLS results, the slope coefficient on delta is positive (coeff.=0.053) and significant. An increase from 25^{th} to 75^{th} percentile in delta is associated with an increase in the probability of being a winner by 2.5%. A positive relation between delta and future performance lends strong support to our Hypothesis 6 that funds with better managerial incentives are associated with better future performance, i.e., more likely to be winners. This result also lends justification to investors' action of directing more money-flows to hedge funds with greater managerial incentives, i.e., higher delta.

Finally, we find the slope coefficient on restriction period to be positive (coeff.=1.534) and significant. Also, the coefficient on lockup period is positive (coeff.=0.083) but not significant. These findings once again lend support to Hypothesis 7, namely funds with greater impediments to capital withdrawals are associated with better future performance, i.e., greater likelihood of being a winner in the future.

B. Alternate measure of performance: Persistence in returns

Earlier in this section, we use returns as a proxy for performance. In this subsection, we capture performance by persistence in future returns and relate it to fund size, past flows, managerial incentives, and lockup and restriction periods. Towards that end, we estimate the following logistic regression:

$$\begin{aligned} Persistent\,Winner_{i,t} &= \theta_0 + \theta_1 Size_{i,t-1} + \theta_2 Flow_{i,t-1} + \theta_3 Delta_{i,t-1} + \theta_4 Lockup_i + \theta_5 Restrict_i + \theta_6 \sigma_{i,t-1} \\ &\quad + \theta_7 I\left(YoungFund_{i,t-1}\right) + \theta_8 I\left(OldFund_{i,t-1}\right) + \theta_9 MFee_i + \sum_{s=1}^{3} \theta_{10}^{s} I(Strategy_{i,s}) + \pi_{i,t} \end{aligned} \quad \textbf{(7)}$$

where, *Persistent* $Winner_{i,t}$ is as defined in Section III. We also estimate the above regression with $Persistent\ Loser_{i,t}$ as the dependent variable.

In Table VII, we report the results from the above regression. For Model 1, the dependent variable is Persistent Winner, where we find that the slope coefficients on size as well as flow are negative (coeffs.= -0.155 and -0.048) and significant. These results are also economically significant. An increase in size from 25th to 75th percentile is associated with a decrease in the probability of a fund being a Persistent Winner by 6.5% (unconditional probability of being a Persistent Winner = 25%). Similarly, an increase in flow from 25th to 75th percentile is associated with a decrease in the probability by 0.8%. As before, size has a stronger influence on the likelihood of a fund being a Persistent Winner in the future. These results lend strong support to Hypothesis 5: larger funds with greater flows are associated with worse future performance.

The coefficient on delta is positive and significant (coeff.= 0.088) in Model 1, implying that higher delta is associated with a higher probability of being a Persistent Winner. An increase in delta from 25th to 75th percentile is associated with an increase in the probability by 4.6%. These results confirm the prediction of Hypothesis 6: funds with greater managerial incentives are associated with better future performance.

The slope coefficient on lockup period is positive (coeff.=0.285) and significant. The coefficient on restriction period is positive (coeff.=1.332) although not significant. These results are consistent with Hypothesis 7: funds with greater impediments to capital withdrawals are associated with better performance, i.e., higher likelihood of being a Persistent Winner.

For Persistent Loser as a dependent variable, our results in Model 2 show that slope coefficient on size is positive (coeff.=0.072) and significant. The slope coefficient on flow is also positive (coeff.=0.036) although not significant. In terms of economic significance, an increase in size from 25th to 75th percentile is associated with an increase in the probability of a fund being a Persistent Loser by 2.7%. Overall, our results suggest that funds with larger size and greater flows are more likely to exhibit consistently poor performance. This finding supports the prediction of Hypothesis 5.

Further, we find the slope coefficient on delta is significantly negative (coeff.=-0.057). An increase in delta from 25th to 75th percentile is associated with a decrease in the probability of being a Persistent Loser by 2.6%. This suggests that better managerial incentives are associated with lower likelihood of a fund being a Persistent Loser. This lends strong support to Hypothesis 6 that funds with higher managerial incentives are associated with better future performance, i.e., lower likelihood of being a Persistent Loser.

The slope coefficient on restriction period is negative (coeff.=-2.459) and significant. The coefficient on lockup period is also negative (coeff.=-0.139) although not significant. These results lend support to Hypothesis 7: Funds with greater impediments to capital withdrawals are associated with better performance, i.e., lower likelihood of being a Persistent Loser.

Overall, the findings in this section confirm that funds with larger size, greater flows, higher managerial incentives, and longer lockup and restriction periods are associated with superior future performance. These results lend strong support to hypotheses 5, 6, and 7.

V. Concluding Remarks

In this paper, we employ a comprehensive database of hedge funds and examine two key questions. The first one investigates the determinants of money-flows into hedge funds. In particular, how does money-flows relate to a fund's past performance (returns and persistence in returns), managerial incentives (delta), and impediments to capital withdrawals (lockup and restriction periods)? We have many new and interesting findings. First, money-flows chase good recent performance and this relation is convex. Second, funds with greater managerial incentives enjoy higher flows, which suggests that investors prefer funds whose managers' interests are aligned with theirs. Third, funds with greater impediments to capital withdrawals (longer lockup and restriction periods) receive lower flows. Finally, funds experiencing higher flows in the past attract greater flows.

The second line of inquiry examines the role of fund size, past flows, managerial incentives, and lockup and restriction periods on the cross-sectional variation in fund performance. Here again we document several new and interesting findings. First, funds with larger size and higher flows are associated with poor future performance. This finding suggests that hedge funds face decreasing returns to scale. Second, funds with higher managerial incentives exhibit superior future performance. Finally, funds with longer lockup and restriction periods are associated with better performance, suggesting that investors in such funds are compensated for the lack of liquidity.

Taken together, these findings significantly improve our understanding of determinants of money-flows, nature of managerial incentives, behavior of investors, and drivers of performance in hedge funds.

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Table I: Breakdown of Funds by Data Sources

Panel A shows the number of hedge funds from the three databases namely HFR, ZCM/MAR, and TASS. Panel B provides the distribution of funds across different strategies. Live funds are those that are operational as of Dec 2000. Dead funds are those that disappeared anytime during our sample period, 1994-2000.

Panel A: Distribution of Hedge Funds across Databases

Source	Live	Dead	ALL
HFR	395	712	1107
TASS	348	221	569
ZCM/MAR	244	486	730
HFR and TASS	205	13	218
HFR and ZCM/MAR	154	41	195
ZCM/MAR and TASS	121	147	268
HFR, ZCM/MAR and TASS	309	35	344
Total	1776	1655	3431

Panel B: Distribution of Hedge Funds across Strategies

Strategy	Live	Dead	ALL
Directional Traders	21%	38%	30%
Relative Value	22%	21%	21%
Security Selection	45%	31%	38%
Multi-Process	12%	10%	11%

Table II: Cross-Sectional Fund Characteristics

This table shows the mean and standard deviations of various fund characteristics during our sample period, 1994-2000. Note that management fee, incentive fee, lockup period, and restriction period do not change over time. The means and standard deviations of the lockup period and restriction period are across the funds that impose these impediments to capital withdrawals.

Fund Characteristics		
Returns (%)	Mean	17.23
	SD	39.88
Volatility (Standard Deviation) (%)	Mean	4.72
	SD	4.03
Age (years)	Mean	4.71
	SD	3.38
Management Fee (%)	Mean	1.22
	SD	0.49
Incentive Fee (%)	Mean	18.24
	SD	5.47
Lockup Period (years)	Mean	0.98
	SD	0.58
Restriction Period (years)	Mean	0.19
	SD	0.07

Table III: Trends in Assets under Management, Flows and Managerial Incentives

Panel A of this table shows the summary statistics of assets under management (AUM) and flows while Panel B provides the summary statistics of the hedge funds that have negative returns and are below high-water mark (HWM). Panel C provides the summary statistics of managerial incentives (delta) across hedge funds as at the beginning, middle, and end of the sample period, i.e. at the end of 1993, 1997, and 2000. Q1 and Q3 indicate the 25th and 75th percentiles.

Panel A

	Summary Statistics	**12/93**	**12/97**	**12/00**
AUM	Total ($bn)	40.7	136.5	201.0
	Mean ($M)	115.0	120.2	135.3
	Q1 ($M)	9.3	10.0	12.1
	Median ($M)	23.3	30.0	38.4
	Q3 ($M)	88.0	89.0	111.0
Flows (%)	Mean	101.1	85.2	53.9
	Q1	-3.2	-11.1	-15.5
	Median	27.8	14.3	4.1
	Q3	108.7	75.9	50.3

Panel B

	Summary Statistics	**12/93**	**12/97**	**12/00**
Funds with negative returns (%)		8.43	12.04	33.12
Negative Returns (%)	Mean	-11.24	-15.22	-19.85
	Median	-7.87	-8.77	-15.04
Funds below HWM (%)		50.20	43.07	51.29
Shortfall for funds below HWM (%)	Mean	-2.85	-3.99	-8.28
	Median	-0.28	-0.00	-1.21

Panel C

	Summary Statistics	**12/93**	**12/97**	**12/00**
Delta ($M)	Mean	0.13	0.17	0.24
	Median	0.03	0.04	0.05

Table IV: Prior returns, incentives, impediments to withdrawal, and money-flows

This table reports average OLS estimates (Fama-MacBeth) using flow as the dependent variable. Flow is the growth rate in the AUM, defined as $(AUM_t - AUM_{t-1}*(1+Returns_t))/AUM_{t-1}$, where AUM_t are the AUM at time t and $Returns_t$ is the hedge fund return in period t. The independent variables include lagged fractional rank quintiles (quintiles of $Rank_{t-1}$), logarithm of lagged delta ($Delta_{t-1}$), lockup period and restriction period in years, lagged flow ($Flow_{t-1}$), lagged size computed as the logarithm of assets under management ($Size_{t-1}$), lagged return volatility ($Volatility_{t-1}$), lagged age dummies for younger (bottom 33% of age) and older (top 33% of age) hedge funds, management fees, contemporaneous returns ($Return_t$), and strategy dummies. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively.

Dependent variable: $Flow_t$

Independent Variables	Expected Sign	Hedge Funds	
		Model 1	Model 2
Intercept		0.262	0.285
$Rank_{t-1}$ - Bottom Quintile		1.006	0.618
$Rank_{t-1}$ - 4^{th} Quintile		0.121	
$Rank_{t-1}$ - 3^{rd} Quintile		1.494^{***}	
$Rank_{t-1}$ - 2^{nd}-4^{th} Quintile			0.747^{***}
$Rank_{t-1}$ - 2^{nd} Quintile		0.178	
$Rank_{t-1}$ - Top Quintile	+	1.798^{**}	1.509^{**}
$Delta_{t-1}$	+	0.011^{*}	0.011^{*}
Lockup Period	-	-0.091^{**}	-0.087^{**}
Restriction Period	-	0.143	0.146
$Flow_{t-1}$	+	0.052^{***}	0.053^{***}
$Size_{t-1}$		-0.129^{***}	-0.128^{***}
$Volatility_{t-1}$		-2.234	-2.260
Younger Fund dummy		0.134^{**}	0.135^{**}
Older Fund dummy		0.007	0.006
Management Fee		-1.784	-1.979
$Return_t$		0.672^{***}	0.678^{***}
Strategy dummies		Yes	Yes
Adjusted R^2		12.9%	13.0%

Table V: Persistence in returns, incentives, impediments to withdrawal, and money-flows

This table reports average OLS coefficient estimates (Fama-MacBeth) using flow as the dependent variable. Flow is the growth rate in the assets under management (AUM), defined as $(AUM_t - AUM_{t-1}*(1+Returns_t))/AUM_{t-1}$, where AUM_t are the AUM at time *t* and $Returns_t$ is the hedge fund return in period *t*. The independent variables include persistence at time t-1, logarithm of lagged delta ($Delta_{t-1}$), lockup period and restriction period in years, lagged flow ($Flow_{t-1}$), lagged size computed as the logarithm of assets under management ($Size_{t-1}$), lagged return volatility ($Volatility_{t-1}$), lagged age dummies for younger (bottom 33% of age) and older (top 33% of age) hedge funds, management fees, contemporaneous returns ($Return_t$), and strategy dummies. Persistent Winner (Loser) is an indicator variable that takes the value 1 if a hedge fund has annual returns above (below) median in its peer group during years, *t-2* and *t-1*. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively.

Dependent variable: $Flow_t$

Independent Variables	Expected Sign	
Intercept		0.612^{**}
Persistent Winner $dummy_{t-1}$	+	0.205^{**}
Persistent Loser $dummy_{t-1}$	-	-0.141^{*}
$Delta_{t-1}$	+	0.013^{*}
Lockup Period	-	-0.048
Restriction Period	-	-0.035
$Flow_{t-1}$	+	0.150^{**}
$Size_{t-1}$		-0.108^{***}
$Volatility_{t-1}$		-1.816^{**}
Younger Fund dummy		0.061
Older Fund dummy		-0.012
Management Fee		-2.101
$Return_t$		0.578^{**}
Strategy dummies		Yes
Adjusted R^2		12.4%

Table VI: Size, prior flow, incentives, impediments to withdrawal, and returns

This table reports average OLS coefficient estimates (Fama-MacBeth) using the returns at time *t* as the dependent variable. This table also reports the logistic regression of WINNER using pooled time-series data. WINNER takes the value 1 if a hedge fund has above-median annual returns in its peer group during year *t*. The independent variables include the lagged size computed as the logarithm of assets under management ($Size_{t-1}$), lagged flow ($Flow_{t-1}$), logarithm of lagged delta ($Delta_{t-1}$), lockup period and restriction period in years, lagged return volatility ($Volatility_{t-1}$), lagged age dummies for younger (bottom 33% of age) and older (top 33% of age) hedge funds, management fees, and strategy dummies. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively.

Independent Variables	Expected Sign	OLS Model 1 $Returns_t$	Logistic Model 2 $WINNER_t$
Intercept		0.158^{***}	0.568^{***}
$Size_{t-1}$	-	-0.012^{**}	-0.107^{***}
$Flow_{t-1}$	-	-0.007^{*}	-0.044^{**}
$Delta_{t-1}$	+	0.005^{***}	0.053^{***}
Lockup Period	+	0.040^{*}	0.083
Restriction Period	+	0.118	1.534^{**}
$Volatility_{t-1}$		0.107	-0.186
Younger Fund Dummy		0.019	0.123
Older Fund Dummy		-0.025^{**}	-0.312^{***}
Management Fee		-0.471	2.602
Strategy Dummies		Yes	Yes
Adjusted / Pseudo R^2		10.6%	1.6%

Table VII: Size, prior flow, incentives, withdrawal impediments, and persistence in returns

This table reports the results of logistic regression using the different performance persistence *dummies* at time *t* as the dependent variable. Persistent Winner (Loser) is an indicator variable that takes value 1 if the hedge fund is a winner (loser) in two consecutive years and 0 otherwise, where a hedge fund is a winner if it has above-median annual returns in its peer group in that year. The independent variables include the lagged size computed as the logarithm of assets under management ($Size_{t-1}$), lagged flows ($Flow_{t-1}$), logarithm of lagged delta ($Delta_{t-1}$), lockup and period and restriction period in years, lagged return volatility ($Volatility_{t-1}$), lagged age dummies for younger (bottom 33% of age) and older (top 33% of age) hedge funds, management fees, and strategy dummies. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively.

Independent Variables	Expected Sign	Persistent Winner Model 1	Expected Sign	Persistent Loser Model 2
Intercept		-0.246		-1.092^{***}
$Size_{t-1}$	-	-0.155^{***}	+	0.072^{*}
$Flow_{t-1}$	-	-0.048^{*}	+	0.036
$Delta_{t-1}$	+	0.088^{***}	-	-0.057^{***}
Lockup Period	+	0.285^{***}	-	-0.139
Restriction Period	+	1.332	-	-2.459^{***}
$Volatility_{t-1}$		-1.645		-6.861^{***}
Younger Fund Dummy		0.227^{*}		-0.223^{*}
Older Fund Dummy		-0.376^{***}		0.238^{**}
Management Fee		6.513		-7.661
Strategy Dummies		Yes		Yes
Pseudo R^2		2.5%		3.4%

Figure 1: Distribution of Hedge Funds by Data Sources

This table shows the percentage of hedge funds from the three databases namely HFR, ZCM/MAR, and TASS at the end of our sample period, i.e., at the end of 2000.

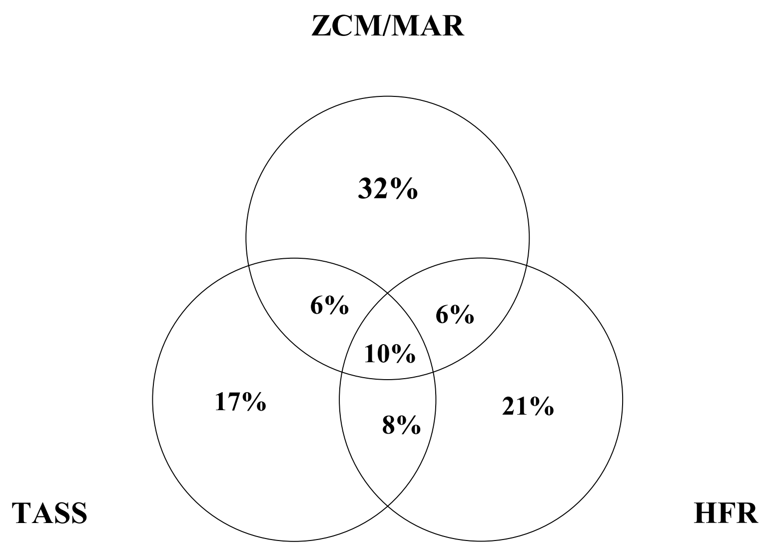
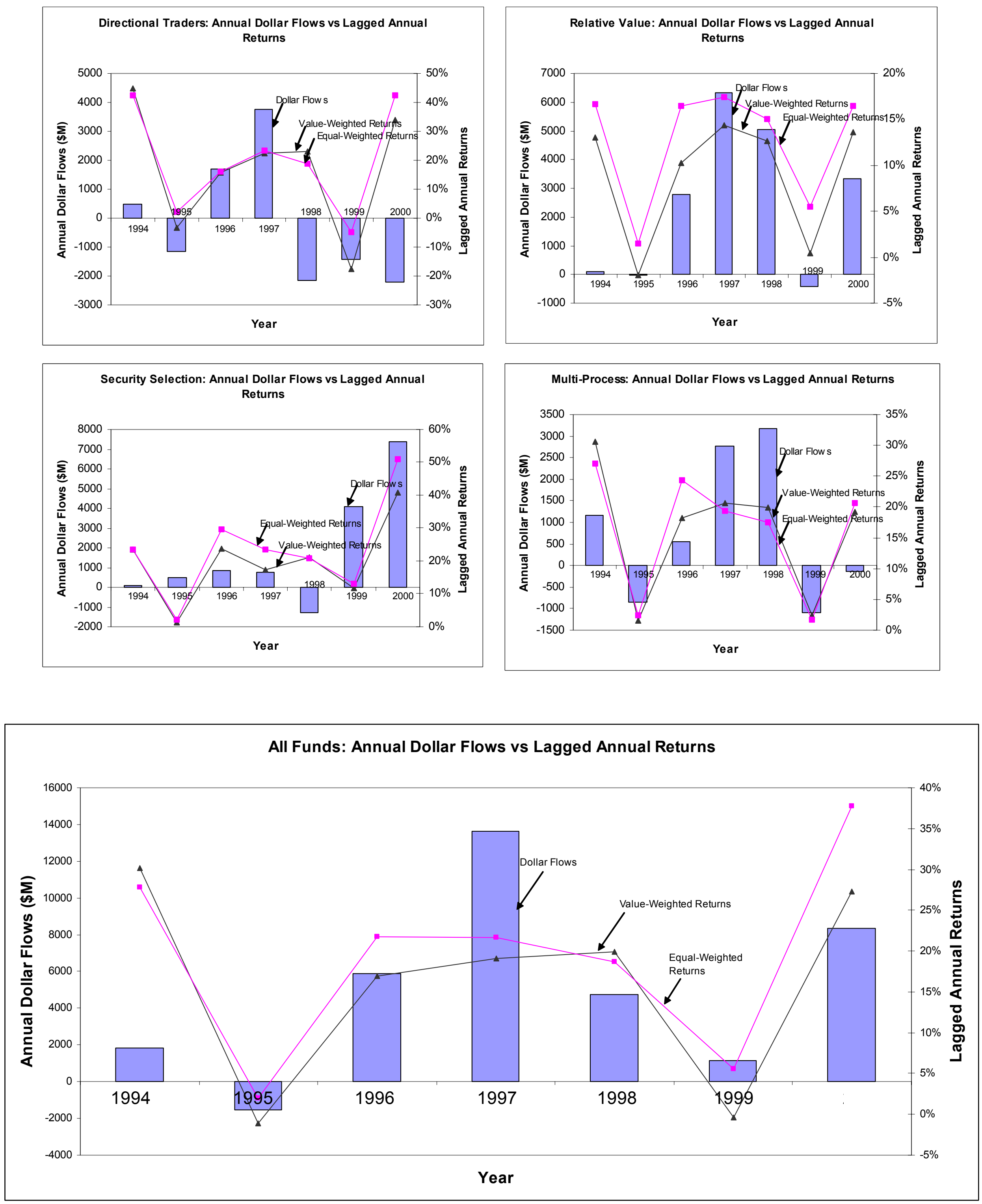


Figure 2: Flows in the Four Strategies as a function of past performance (1994-2000)

This figure plots the annual flows in millions of dollars with the lagged annual returns for all the funds belonging to the four strategies and "All Funds" from 1994 to 2000.



Appendix A: Classification of Hedge Fund Strategies

This table provides the mapping of the strategies provided by different data vendors with the four broad strategies that we use in our study. It also provides a brief definition of each of the four broad strategies.

Source	Vendor's Strategy	Broad Strategy
HFR, ZCM/MAR and TASS	Convertible Arbitrage	Relative Value
HFR, ZCM/MAR	Distressed Securities	Multi-Process
HFR, ZCM/MAR and TASS	Emerging Markets	Directional Traders
HFR, ZCM/MAR and TASS	Equity Hedge	Security Selection
HFR, ZCM/MAR	Equity Non-Hedge	Security Selection
HFR, ZCM/MAR and TASS	Event Driven	Multi-Process
HFR, ZCM/MAR and TASS	Fixed Income	Relative Value
HFR	Foreign Exchange	Directional Traders
ZCM/MAR	Global Established	Security Selection
ZCM/MAR	Global International	Security Selection
HFR, ZCM/MAR and TASS	Macro	Directional Traders
HFR, ZCM/MAR and TASS	Market Neutral	Relative Value
HFR, ZCM/MAR	Market Timing	Directional Traders
HFR, ZCM/MAR	Merger Arbitrage	Relative Value Traders
HFR, ZCM/MAR and TASS	Relative Value Arbitrage	Relative Value Traders
HFR, ZCM/MAR	Sector	Directional Traders
HFR, ZCM/MAR and TASS	Short Selling	Directional Traders
HFR, ZCM/MAR	Statistical Arbitrage	Relative Value

Directional Traders usually bet on the direction of market prices of currencies, commodities, equities, and bonds in the futures and cash markets.

Relative Value strategies take positions on spread relations between prices of financial assets or commodities and aim to minimize market exposure.

Security Selection managers take long and short positions in undervalued and overvalued securities respectively and reduce the systematic market risks in the process. Usually, they take positions in equity markets.

Multi-Process strategy involves multiple strategies employed by the funds usually involving investments in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations and share buybacks. For example, the portfolio of some Event-Driven managers may shift in majority weighting between Merger Arbitrage and Distressed Securities, while others may take a broader scope.

Appendix B: Computation of Delta

We compute of the dollar flows from the investors for each fund and each year. For each year's dollar flow, we compute the option delta separately at the end of each year. We sum these deltas to determine the total fund delta for the assets under management of each fund at the end of each year. The exercise price of the option on each annual flow depends on its high-water mark level and hurdle rate. For dollar outflows, we follow a FIFO (first-in, first-out) policy. Using Black and Scholes (1973) formula, we estimate the dollar change in the manager's performance-related incentive fee for a one percent change in asset value. In particular, we compute delta as

$$\text{delta} = N(Z)*(S*0.01)*I$$

where $Z = [\ln(S/X) + T(R+\sigma^2/2)]/[\sigma*T^{0.5}]$
S = Spot price
X = Exercise price
T = Time to maturity of the option in years (one year)
R = Risk-free rate of interest
σ = Volatility of monthly returns over the year
$N(\,)$ = Cumulative density function of a standard Normal distribution
I = Incentive fee expressed as a fraction

Appendix C: Following GIR (2003) approach for only offshore funds in our sample

This table reports the regressions of flow on the performance in the previous year following Goetzmann, Ingersoll, and Ross (GIR) (2003). As in GIR (2003), the results are for the sub-sample of offshore funds for the period, 1990-1995. Figures marked with ***, **, and * are significant at the 1%, 5%, and 10% respectively.

Independent Variables	1990	1991	1992	1993	1994	1995	F-M	Model 1	Model 2
Intercept	-0.802***	-0.951***	-0.697**	-0.606**	-0.789*	-0.173	-0.670***	-0.328*	-0.029
$Rank_{t-1}$ – Bottom Quintile	-1.025	0.902	-0.472	1.144	1.999	1.398	0.658	1.023	
$Rank_{t-1}$ - 4th Quintile	1.704	2.402	2.641	-0.786	-0.133	-1.868	0.660	-0.007	
$Rank_{t-1}$ - 3rd Quintile	-0.085	-1.849	-0.340	3.070	-0.795	-0.339	-0.056	-0.005	
$Rank_{t-1}$ - 2nd Quintile	-0.289	0.767	1.475	-1.704	3.229	0.885	0.727	0.946	
$Rank_{t-1}$ -Top Quintile	0.181	1.490	-2.252	1.461	0.759	5.516	1.192	1.943	
Lagged Return									0.106
Year Dummies								Yes	Yes
Adjusted R^2	-3.0%	1.6%	2.4%	-0.6%	2.3%	-0.1%	0.4%	2.4%	1.6%