Investor Flows and Share Restrictions in the Hedge Fund Industry

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Abstract

This paper studies the effect of share restrictions on the flow-performance relation of individual hedge funds. As such, we reconcile previous research that shows conflicting results for this relation. Specifically, we find that hedge funds exhibit a convex flow-performance relation in the absence of share restrictions (similar to mutual funds), but exhibit a concave relation in the presence of restrictions—our evidence is consistent with both a direct effect of restrictions and an indirect effect that is due to endogenizing of restrictions by investors. Further, we find that the "live database" exhibits a concave flow-performance relation due to capacity constraints, but that the "defunct database" displays a convex relation due to the extreme (good and bad) performing funds that populate this database. Finally, we find that money is smart, that is, fund flows predict future hedge fund performance; however, this smart money effect is reduced among funds with share restrictions.

Key words: hedge fund flows, share restrictions, asset illiquidity, smart money effect
JEL classification: G23, G11

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I. Introduction

It is estimated that over $1.2 trillion is now managed by hedge funds, with substantial additional sums flowing into this industry each year.[1] Accordingly, it is important to understand the behavior of investor flows in hedge fund sectors, since flows often motivate hedge fund trading activity and, therefore, may provide insights into the potential for hedge funds to destabilize markets.

Although the behavior of mutual fund flows is well-documented,[2] hedge funds have proven much more elusive. Besides the difficulty in obtaining complete data that is free of reporting biases, hedge funds exhibit many complex features that impact flows, relative to mutual funds. For example, common hedge fund characteristics include restrictions on the number of investors, high minimum investments, lock-up periods, forced redemption, closure to new investments, capacity constraints, asset illiquidity, and required delay periods for subscriptions and redemptions. The impact of such restrictions on the behavior of flows, while likely important, has largely been ignored by past hedge fund research. Simply put, it is not clear how the presence of share restrictions may affect the reaction of investors to the perceived management quality of hedge funds that is represented by their past performance.

Accordingly, this paper examines the structural features of individual hedge funds, and the influence of these features on the flow-performance relation of the funds. While some previous studies have analyzed the flow-performance relation without specifically considering these structural features, they have found conflicting results. For example, Agarwal, Daniel, and Naik (2004) find a convex flow-performance relationship for individual hedge funds, which is similar to that documented for individual mutual funds by Chevalier and Ellison (1997) and Sirri and Tufano

[1] Chicago-based Hedge Fund Research, Inc. (HFR) estimates total hedge fund industry assets of $1.225 trillion at the end of the second quarter of 2006.
[2] For example, Sirri and Tufano (1998) and Chevalier and Ellison (1997) find that the best performing mutual funds receive disproportionately more flows than other funds.

(1998). By contrast, Goetzmann, Ingersoll and Ross (2003) and Getmansky (2005) find a concave flow-performance relation, while Baquero and Verbeek (2005) find a linear relation. We argue that the existence of restrictions on flows, as well as differences in hedge fund characteristics that are included in live versus defunct databases explain these differing results.

Specifically, in this paper, we consider how subscription periods, capacity restrictions, closure to new investment, certain onshore fund restrictions (such as a limit on the allowable number of investors), lockup periods, redemption periods, and implicit restrictions driven by illiquidity in the assets held by hedge funds impact the flow-performance relation in various portions of the performance spectrum (low, middle, or high past-performing funds). Moreover, we take into account investor anticipation of future binding restrictions when they make their investment decisions—that is, investor endogenizing of hedge fund restrictions.

In the absence of restrictions, we find that the flow-performance relation for individual hedge funds is convex, similar to that observed for mutual funds. However, the presence of significant restrictions leads to a concave flow-performance relation through two competing effects. First, the "direct effect" of restrictions reduces the flow-performance slope in both the low-performance (due to restricted outflows) and high-performance (due to restricted inflows) regions. However, the "indirect effect" of investor endogenization of restrictions increases the slope in both regions, due to a reduction of inflows to low-performance funds and a reduction of outflows from high-performance funds, respectively. We find that the indirect effect dominates in the low-performance region, while the direct effect dominates in the high-performance region, resulting in a concave flow-performance curve.

We also use a proxy for the liquidity of the underlying portfolio holdings of hedge funds to study the relation between liquidity and both implicit and explicit flow restrictions. We find that our liquidity proxy (θ_0) is highly correlated with all explicit share restrictions, except onshore domicile, indicating that hedge fund managers indeed consider asset illiquidity when implementing share restrictions.[3] Further, we find that our asset liquidity measure serves as a proxy for implicit (undisclosed) share restrictions, since it explains changes in the shape of the flow-performance relation, controlling for explicit restrictions.

Next, we explicitly consider hedge funds belonging to live versus defunct fund databases to determine the differences in the flow-performance relation between these two subsamples. We find that the flow-performance relation for live funds is concave, due to high-performing funds voluntarily closing to new investments, hence reducing the fund flow sensitivity in this region. In contrast, the flow-performance relation is convex for defunct funds because better-performing defunct funds have voluntarily withdrawn from the "live" database, while truly failed funds have been liquidated.

Finally, we examine whether investor flows are "smart," that is, whether flows can predict future hedge fund performance. Prior studies of mutual funds (Gruber (1996) and Zheng (1999)) suggest that investors have selection ability. However, few studies examine the smart money effect among hedge funds—Barquero and Verbeek (2005) study the performance of aggregate fund flows, but do not find any evidence of a smart money effect at this level for various time horizons. We approach this issue by examining the selectivity of all hedge fund investors, as well as investors in subgroups of funds.

We find evidence that investor flows predict performance, i.e., that money is "smart." In particular, funds that experience net inflows outperform those that experience net outflows. Further, we find evidence that the smart-money effect is reduced by share restrictions among hedge funds. Specifically, a zero-cost, equally-weighted portfolio that is long funds with positive flows in

[3] The asset illiquidity proxy (θ_0) measure was developed by Getmansky, Lo and Makarov (2004) for hedge funds. It proxies for both asset illiquidity and return smoothing.

the prior quarter and short funds with negative flows in the prior quarter generates a statistically significant alpha of 2.08% per month for funds with high θ_0, i.e., funds that have higher asset liquidity and relatively few share restrictions. By contrast, this long-short portfolio generates an insignificant alpha among funds having low asset liquidity and significant share restrictions.

Overall, our results indicate that the flow-performance relation for hedge funds is quite different from that of mutual funds due to the many restrictive features of hedge fund markets. Flow restrictions lead to a concave flow-performance relation, which contrasts strongly with the convex relation found in the mutual fund literature, and is consistent with the ability of investors to anticipate and endogenize restrictions in their investment choices. As such, our paper reconciles prior findings on the flow-performance relation among hedge funds, and provides new insights on the behavior of capital among individual hedge funds. In turn, our findings provide a foundation for studying the behavior of aggregate capital among different hedge fund styles in order to study such macro issues as the role of hedge funds in financial market contagion.

The rest of our paper is organized as follows. Section II develops hypotheses to be tested in the data. Section III describes the data. Methodology is developed in Section IV. We report empirical results in Section V, and conclude in Section VI.

II. Hypotheses

Investor money flows are strongly correlated with the past performance of hedge funds, which indicates that investors infer fund manager talent at least partly from past performance. This evidence is similar to the reaction of flows to mutual fund performance.

We conjecture that the unique restrictions and other features present in the hedge fund industry significantly affect the shape of the flow-performance relation for individual funds, making it (in many cases) much different from that of individual mutual funds, which have relatively few flow restrictions. Moreover, the presence of share restrictions and asset illiquidity may limit the ability of investors to capitalize on the information about hedge fund quality that is represented by prior performance.

For instance, most hedge funds implement lockup provisions, subscription, redemption, and advance notice periods that delay or otherwise limit the responsiveness of fund flows to performance. These restrictions are further complicated by onshore and offshore structures. Specifically, U.S.-based (onshore) funds are allowed to cater only to "sophisticated" investors having a minimum of $1 million in financial assets.[4] Moreover, onshore funds are not allowed to advertise to the general public, and differences in legal structures caused by tax provisions and the limit of 500 investors per each onshore hedge fund also lead to more severe share restrictions relative to offshore funds.[5] All of these restrictions may affect the flow-performance relation of hedge funds.

Hedge fund strategies are also fundamentally different from the long-only portfolio strategies implemented by mutual funds (Fung and Hsieh (1997), Liang (1999), Goetzmann, Ingersoll and Ross (2003)). For instance, hedge funds often engage in arbitrage opportunities. By their very nature, arbitrage opportunities are not infinitely exploitable—resulting in limits to fund flows, even to the most successful hedge funds. Hedge funds that have reached their optimal level of assets (which are usually better performing funds) may close to new investments and voluntarily withdraw from disclosing to public databases, as they no longer have the need to market their funds.

Moreover, unlike mutual funds, hedge funds—especially distressed security and emerging market funds—tend to invest in illiquid securities. To address these issues, most hedge funds likely have additional contingent restrictions on flows that are written in investor contracts, but not

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[4]As of February 2007, the Securities Exchange Commission proposed to increase the limit to $2.5 million in financial investments.

[5] Onshore funds are usually organized as limited partnerships and offshore funds are usually organized as open ended investment companies. Partnerships are usually more illiquid than open ended investment companies and have higher share restrictions (Liang and Park, 2007).

explicitly denoted in public hedge fund databases (such as TASS). In this paper, we adopt Getmansky, Lo, and Makarov (2004)'s θ_0 measure for capturing asset illiquidity, which we use to proxy for restrictions.

Investors may also endogenize the presence of investment restrictions when they react to past performance. For instance, an investor may be reluctant to invest in a fund with few liquid assets, such as a fund experiencing large outflows, since that investor may be restricted from withdrawing money at a later date. The endogenizing of restrictions may further impact the flow-performance relation, relative to mutual funds.

In summary, inflows and outflows for hedge funds are restricted, while those for mutual funds generally are not (with the exception of the small number of mutual funds that close to new investors). In addition, the cross-section of hedge funds contains widely differing flow restrictions, making this a fertile area to study the types of restrictions that are most likely to change the fund flow-performance relation. Finally, investor endogenizing of flow restrictions may further impact hedge fund flows. These issues can potentially modify the fund flow-performance relation from that of mutual funds, as well as create large cross-sectional differences in this relation among hedge funds.

In general, we conjecture that fund flows to hedge funds exhibit quite different sensitivities to past performance, compared to mutual funds, due to the much larger array of restrictions that prevent flows from responding quickly to past performance. The past literature on hedge fund flows finds widely differing evidence regarding our conjecture.[6] These papers attribute their opposing results to the use of different hedge fund databases and time periods. However, none of

[6] For example, Agarwal, Daniel, and Naik (2004) find a convex relationship in the flow-performance relationship for individual hedge funds, which is similar to that documented for individual mutual funds by Chevalier and Ellison (1997) and Sirri and Tufano (1998). By contrast, Goetzmann, Ingersoll and Ross (2003) and Getmansky (2005) find a concave relationship in the flow-performance relationship, while Baquero and Verbeek (2005) find a linear fund flow-performance relationship.

the past literature has explicitly studied the impact of share restrictions and asset illiquidity on the fund flow-performance relation.

We conjecture that there are two effects of restrictions on investor flows. The first effect, which we call the "direct effect," is the binding effect of restrictions on flows which restricts flows due subscription and redemption restrictions. The second effect, which we call the "indirect effect," captures investors' anticipation of future binding restrictions and endogenizes these restrictions in investment decisions. We consider a possibility of each effect for low and high-performance regions.

In the low-performance region, the direct effect of restrictions on withdrawals (i.e., redemption, advance notice and lockup periods and asset illiquidity) will be binding and decreasing the sensitivity of the flow-performance function in this region. In the presence of the indirect effect, investors may anticipate the possibility of future restrictions on outflows among poorly performing funds, and, therefore, reduce their (contrarian) inflows to such funds, thus increasing the slope of the flow-performance curve in that region. Thus, the direct effect of restrictions reduces the slope of the flow-performance curve in the low-performance region, while the indirect effect increases the slope.

In the high-performance region, the direct effect ensures that investors cannot put inflows into funds with binding restrictions (i.e., subscription period, capacity constraint, decision to close and onshore provisions), which are likely to be the highest performers.[7] However, the indirect effect is that investors anticipate future restrictions on inflows, and, thus, decrease their (contrarian) outflows from well-performing funds. Thus, the direct effect of restrictions reduces the slope of the flow-performance curve in the high-performance region, while the indirect effect increases this slope.

[7]Agarwal, Daniel, and Naik (2004), Goetzmann, Ingersoll and Ross (2003), Getmansky (2005) and Baquero and Verbeek (2005) find that investors preferentially invest more into higher performing funds in the absence of restrictions.

Our hypotheses recognize these two competing effects, and our empirical tests examine which effect, direct or indirect, seems to have a larger impact on the flow-performance relation in the low- and high-performance regions.

To be specific, we consider the following hypotheses about the relation between flow and performance due to restrictions, noting that they are not mutually exclusive in the sense that the two hypotheses may work independently:

Hypothesis 1A (Direct Effect of Share Restrictions and Asset Illiquidity): Significant share restrictions and asset illiquidity lead to a decrease in outflows from poorly performing funds, and a decrease in inflows to well-performing funds due to the binding nature of these restrictions for extreme flow funds. The result is a flatter flow-performance relation in both the low- and high-performance regions of the curve.

Hypothesis 1B (Indirect Effect of Share Restrictions and Asset Illiquidity): Investors anticipate the potential future binding effect of share restrictions by reducing their inflows to poorly performing funds and reducing their outflows from well-performing funds. This anticipation effect results in a steeper flow-performance relation in the low- and high-performance regions of the curve.

Based on the above hypotheses, we conjecture the following about the flow-performance relationship that may be tested using the TASS hedge fund database.

Prediction 1 (Concave Flow-Performance Relationship in the Presence of Restrictions): In the low-performance region, the indirect effect prevails as investors successfully endogenize known binding restrictions. In the high-performance region, investors find it difficult to endogenize unexpected hedge fund manager actions, leading to a dominant direct effect. This leads to a concave flow-performance relationship in the presence of restrictions.

In the low-performance region, investors can easily anticipate restrictions—such as lock-up provisions, advance notice periods, and redemption periods—which are directly observable and clearly specified in investment contracts. Therefore, we predict that investors will be able to endogenize these specific restrictions, which are more relevant for low-performance regions. On the other hand, hedge fund managers may unexpectedly close their funds due to capacity constraints, which vary substantially across different asset classes and fund structures. Since these restrictions are not clearly outlined in investment contracts, investors are less likely to be successful in anticipating the binding effect of such inflow restrictions. Therefore, we predict that the direct effect dominates in the high-performance region in the presence of restrictions.[8] Taken together, the presence of restrictions leads to a concave fund flow-performance relation.

Prediction 2 (Convex Flow-Performance Relationship in the Absence of Restrictions): In the absence of restrictions, the best performing funds command a disproportionate flow share, leading to a convex fund flow-performance relationship.

Our next hypothesis explores potential differences in the fund flow-performance relation between the Live and Defunct databases. Many funds in the high-performance region of the Live database are capacity-constrained, and, therefore, closed to new investment, reducing the flow-performance sensitivity in this region. This effect results in a concave flow-performance relation. Conversely, the flow-performance relation for funds in the Defunct database is convex since exceptionally poorly performing funds experience extreme outflows and liquidate, and exceptionally well-performing funds experience extreme inflows and often withdraw from the data vendor (since the fund no longer needs the publicity, and may prefer to reduce its public disclosure).

<u>Hypothesis 2 (Live vs. Defunct Funds):</u> Funds in the Live database exhibit a concave fund flow-performance relation due to better performing fund closures to new investment. Conversely, funds in the Defunct fund database exhibit a convex fund flow-performance relation due to the presence of extremely well-performing funds that have attracted substantial new investments and poorly-performing funds that have liquidated.

[8] The only restriction which is predetermined in investment contracts and is relevant in the high-performance region is a subscription period. However, we anticipate and show in the paper that the effect of endogenizing this restriction is clearly dominated by other inflow restrictions.

Our final hypothesis analyzes the effect of inflow and outflow restrictions faced by hedge fund investors on the "smart money" effect, that is, the ability of hedge fund investors to move money into future winners and out of future losers. If money is smart, meaning that current fund flows can predict future fund returns, then the direct effect of restrictions on both inflows and outflows is to reduce the ability of flows to predict following-period hedge fund returns, since investors cannot fully respond to their superior information. For example, outflow restrictions such as lockup periods or redemption periods may delay the ability of investors to respond to poor performance when they gather information that indicates that fund performance will worsen.

<u>Hypothesis 3 (Effect of Restrictions on Smart Money):</u> Restrictions on hedge funds will result in a reduced "smart money" effect. Specifically, restrictions on investing in (withdrawing from) hedge funds will lead to a lower (higher) future performance of inflows (outflows).

III. Data

A. TASS Database

We use the Lipper/TASS database (hereafter, TASS) for our empirical analysis. As of the third quarter of 2005, this database tracks $800 billion held by global single-manager hedge funds, excluding funds of funds. These numbers exclude money held in separately managed accounts. There are other databases like AltVest, CISDM/MAR, and Hedge Fund Research (HFR). However, the TASS[9] database is probably the most comprehensive database covering hedge funds according to academic studies[10].

The TASS database consists of monthly returns, assets under management, and other fund-specific information. TASS also classifies hedge funds into 11 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 and Fund of Funds. The database is divided into two parts: "Live" and "Graveyard" funds (hedge funds that are in the "Live" database are active as of September, 2005). Once a hedge fund decides not to report its performance, is liquidated, restructured, or merged with other hedge funds, the fund is transferred into the "Graveyard" database from the "Live" database.

Because the TASS database represents returns and asset information for live and defunct funds, the effects of survivorship bias are minimized.[11] However, the database is subject to backfill bias; specifically, when a fund decides to be included in the database, TASS adds the fund to the "Live" database and backfills all available prior performance data for the fund.[12] Because the

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

[10] Not all hedge funds report to the TASS database. Also, there are separate accounts, which are not reported to hedge fund databases. These separate accounts absorb a good portion of alternative investment fund flows.

[11] Survivorship bias in hedge fund performance has been well documented by Fung and Hsieh (2000) and Liang (2000).

[12] Also, due to reporting delays, some "Graveyard" funds can be incorrectly listed in the "Live" database. TASS adopted a policy of transferring funds from the "Live" to the "Graveyard" database if its managers have not heard from hedge funds or were not able to contact the hedge fund managers over a 6-8 month period.

"Graveyard" database became active in 1994, thus funds that were dropped from the "Live" database before 1994 were not recorded by TASS, the database is subject to some degree of survivorship bias.[13]

As of September 2005, the combined database of both live and defunct hedge funds contained 6,097 funds having at least one monthly return observation. Out of these, 6,097 funds, 3,821 funds are in the Live database, with 2,276 in the Graveyard database.

The majority of the 6,097 funds report returns, net of management and incentive fees, on a monthly basis.[14] TASS converts all foreign-currency denominated returns to US-dollar returns using the appropriate exchange rates. TASS also reports assets in local currency and reports returns using local currency NAV.

We eliminated 54 funds that reported only gross returns, leaving 6,043 funds in the "Combined" database (3,797 in the Live and 2,246 in the Graveyard database). The Graveyard database starts in 1994; therefore, to adjust our sample for the survivorship bias, we only consider funds with time-series of returns starting in 1994. As a result, we are left with 6,017 funds in the "Combined" database (3,792 in the Live and 2,225 in the Graveyard databases).

Furthermore, we threw out observations in the beginning and the end of a fund time series that did not have any assets under management reported. We further eliminated stale price observations of more than a quarter. Furthermore, we eliminated the funds with less than 12 months of observations. If a fund had one month of missing assets under management, we interpolated the missing observation. If a fund reported assets in discrete intervals, we would

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[13] For studies attempting to quantify the degree and impact of survivorship bias, see Brown, Goetzmann, Ibbotson, and Ross (1992), Brown, Goetzmann, and Ibbotson (1999), Brown, Goetzmann, and Park (2001), Carpenter and Lynch (1999) and Fung and Hsieh (1997, 2000), and Liang (2000).

[14] TASS defines returns as the change in net asset value during the month (assuming the reinvestment of any distributions on the reinvestment date used by the fund) divided by the net asset value at the beginning of the month, net of management fees, incentive fees, and other fund expenses. Therefore, these reported returns should approximate the returns realized by investors.

observe the largest continuous interval. Finally, we have 4,594 funds left after all filtering (75% of the initial fund sample).

IV. Methodology

A. Measuring the Flow-Performance Relation

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

$$\begin{gathered} \text{Trank}^1 = \text{MIN}(1/3, \text{Frank}) \\ \text{Trank}^2 = \text{MIN}(1/3, \text{Frank} - \text{Trank}^1) \\ \text{Trank}^3 = \text{MIN}(1/3, \text{Frank} - \text{Trank}^1 - \text{Trank}^2) \end{gathered} \tag{1}$$

We measure flows as a proportion of assets by the year *t* change in net assets, adjusted for investment returns:

$$Flow_t = \frac{Assets_t - Assets_{t-1}(1+r_t)}{Assets_{t-1}} \ . \tag{2}$$

The top 1% of flows are winsorized to prevent outliers from affecting our analysis. The following regression is specified to understand the determinants of fund flows:

$$\begin{aligned} Flow_{i,t} &= \alpha_i + \beta_1 Trank^1_{i,t-1} + \beta_2 Trank^2_{i,t-1} + \beta_3 Trank^3_{i,t-1} + \beta_4 SD_{i,t-1} + \beta_5 Assets_{i,t-1} \\ &+ \beta_6 Live_i + \beta_7 AdvanceNoticePeriod_i + \beta_8 OpentoPublic_i + \beta_9 HighWaterMark_i \\ &+ \beta_{10} Leverage_i + \beta_{11} ManagementFee_i + \beta_{12} IncentiveFee_i + \beta_{13} LockupPeriod_i \\ &+ \beta_{14} RedemptionPeriod_i + \beta_{15} SubscriptionPeriod_i + \beta_{16} StyleEffect_i \end{aligned} \tag{3}$$

where $SD_{i,t-1}$ is standard deviation of returns at time t-1, $Assets_{i,t-1}$ is natural logarithm of hedge fund dollar assets at time t-1, $Live_i$ is a Live Dummy (1 if a fund is in the live database and 0 if a fund is in the defunct database), $AdvanceNoticePeriod_i$ is Advance Notice Period for redeeming money (measured in days), $OpentoPublic_i$ is an open to public dummy (1 if a fund is open to public and 0 otherwise), $HighWaterMark_i$ is a high water mark dummy (1 if a high water market provision is present and 0 otherwise), $Leverage_i$ is a leverage dummy (1 if a fund uses leverage and 0 otherwise), $ManagementFee_i$ is the management fee (measured as a percentage of assets under management), $IncentiveFee_i$ is the incentive fee (measured as a percentage of a fund's upside above a specific threshold), $LockupPeriod_i$ is the lockup period (measured in months), $RedemptionPeriod_i$ is the redemption period (measured in days), $SubscriptionPeriod_i$ is the subscription period (measured in days) and Style $Effect_t$ is the average flow for a particular category at time *t*. To further study the impact of share restrictions on the flow-performance relation in Equation (3), we add interaction terms between performance ranks (low, middle, and high) and restriction dummy variables (subscription and redemption periods, advance notice period, lockup, onshore vs. offshore, asset illiquidity, and capacity restrictions).[15]

Annual data from 1994 through 2004 is used. The regression is specified for hedge funds, funds of funds, and for each strategy individually. Moreover, the total sample is separated into Live and Defunct sub-samples, and the performance-fund flow relationship is analyzed for the Combined, Live and Defunct samples.

B. Measuring Asset Illiquidity and Smoothing

To quantify the impact of asset illiquidity and smoothing on hedge fund returns, we follow Getmansky, Lo and Makarov (2004) by asserting that a fund's true economic return in month *t* is

[15] The restriction dummy variables are defined as zero if low restriction (parameter value equal to or below the median) and one if high restriction (parameter value above the median).

given by R_t, which represents the sum total of all the relevant information that would determine the equilibrium value of the fund's securities in a frictionless market. The authors assume that true economic returns are not observed. Instead, R_t^0 is a reported and observed monthly return in period *t*, and let:

$$\begin{aligned} &R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2} \\ &\theta_j \in [0,1],\ j = 0,1,2 \\ &\theta_0 + \theta_1 + \theta_2 = 1 \end{aligned} \tag{4}$$

which is a weighted average of the fund's true monthly returns R_t over the most recent 3 months, including the current month. θ_0, θ_1 and θ_2 are estimated using a maximum likelihood procedure. θ_0 is an asset illiquidity and smoothing measure. If θ_0 for a specific hedge fund is close to 1, then most of the real contemporaneous return is currently reflected in the observed data, thus, the hedge fund exhibits more liquidity and a lack of smoothing. However, a smaller θ_0 signifies that a hedge fund is illiquid and is more likely to exhibit smoothing. Following Getmansky, Lo and Makarov (2004), we impose a 5-year filter in order to obtain reliable θ_0, θ_1 and θ_2 estimates.

C. Measuring the Performance of Flows

C.1. GT Measure

First adopted in Grinblatt and Titman (1993), the *GT* measure is a performance measure that does not require the knowledge of the benchmark for the evaluated investment portfolio, which is especially appropriate for hedge funds because hedge funds tend to follow absolute versus relative benchmark strategies, adopt dynamic trading strategies and invest in various asset classes. In applying the *GT* measure for the performance of hedge fund flows, we assume that investors as a whole rebalance their hedge fund portfolios on a quarterly basis, the portfolio weight of which for a fund is determined by its assets.[16]

$$GT_{t+1} = \sum_{i=1}^{N} (w_{i,t} - w_{i,t-1}) \cdot R_{i,t+1} \qquad (5)$$

where $w_{i,t}$ and $w_{i,t-1}$ are the weights of fund i measured by assets at the beginning of quarters t and $t-1$, respectively, and $R_{i,t+1}$ is the raw return of hedge fund i for quarter t, and N represents the number of hedge funds in quarter t. If hedge fund investors are smart in allocating their capital across hedge funds, we expect to see a significantly positive average GT measure over the sample period.

C.2. An Index Model to Measure the Performance of Flows

Considering the complexity in the strategies that might be pursued by hedge funds, we run the following multi-index model to test the performance of flows into hedge funds.[17] Included in the independent variables are the Russell 3000 index return, difference between the Russell 1000 index return and the Russell 2000 index return (LMS), difference between the Russell 1000 value index return and the Russell 1000 growth index return (VMG), the momentum factor downloaded from Ken French's web site (UMD), the Lehman Aggregate Bond index return, yield spread between BAA bonds and AAA bonds, yield spread between the 10-year Treasury note rate and the 6-month LIBOR, return on the S&P500 at-the-money call option,[18] the MSCI emerging market stock index return, the MSCI emerging market bond index return, the 6-month LIBOR, the Federal Reserve dollar index return, the gold index return, oil price change, and change in the volatility index (VIX). The intercept of the model is supposed to measure the abnormal performance of hedge

[16] A similar approach is used by Zheng (1999) for measuring the performance the mutual fund flows.
[17] Similar multi-index models are used in Liang (1999), Agarwal and Naik (2004), and Fung and Hsieh (2004).
[18] We thank Vikas Agarwal and Narayan Naik for kindly providing the option-based factor data, an earlier version of which was used in Agarwal and Naik (2004).

funds after all known risk factors are accounted for. The beta coefficients of the independent variables illustrate the exposure of the hedge fund return to the market indexes.

V. Results

A. Descriptive Statistics and Univariate Analysis

Table I provides an overview of the returns for each of the 11 styles from 1994 through 2004. Long/Short equity hedge style represents 40% (the highest concentration per style) of hedge funds in the database. Panels A, B, and C display statistics for combined, live, and defunct funds, respectively. In each panel, statistics are provided for the equally-weighted portfolio of hedge funds within each category, as well as for an asset-weighted portfolio.[19] For example, Panel A shows that different categories of funds exhibit quite different return moments: the long/short equity category earns the highest mean return of 1.06% per month, in contrast to -0.16% for the short seller category. Not surprisingly, emerging market, short sellers, and managed futures have higher average standard deviations than other funds, consistent with the fact that these funds engage in riskier trading strategies due to derivatives, short selling, and emerging market investments. Jarque-Bera (JB) tests also reject that emerging market, event driven, and fixed income arbitrage fund returns are not normally distributed.

< Insert Table I >

Several hedge fund categories display very large higher moments. For example, fixed income arbitrage funds display a negative skewness of -0.88 and a kurtosis of 7.14, consistent with these hedge funds implementing strategies that are more event-driven and, therefore, capture non-linearities in prices around such events.

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[19] AWR is the asset-weighted return using the last available assets under management for a hedge fund as an asset weight. We also computed, but not tabulated the asset-weighted return using the average assets under management for a hedge fund as an asset weight over the period of 1994 to 2004.

An average first order serial correlation coefficient, which is a proxy for illiquidity is 10%. Consistent with Getmansky, Lo and Makarov (2004), hedge fund categories that hold and trade illiquid assets have the highest first order serial correlation coefficients: (convertible arbitrage (32%), emerging markets (16%), event driven (19%) and fixed income arbitrage (15%)). Multi-strategy and fund of funds have also high levels of autocorrelation (14% and 23%, respectively).

Further insights are apparent when examining live and defunct fund return moments in Panels B and C. Specifically, an equally-weighted portfolio of live funds has a much higher mean return (1.10%) than that of defunct funds (0.53%). This is consistent with Liang (2000), who shows that poor performance is the main reason for hedge fund attrition. Live funds are also less risky (with a mean standard deviation of 3.51%) than defunct funds (5.42%). Consistent with Brown, Goetzmann, Ibbotson, and Ross (1992), defunct funds take riskier bets, and, hence, are more likely to disappear because of the relation between extreme poor performance and fund attrition. The average autocorrelation coefficient is twice as high for live funds (13%) compared to defunct funds (7%). This is consistent with the finding that funds earn an excess return due to illiquidity exposure (Aragon, 2007) and these funds are more likely to survive.

<Insert Table II >

Table II reports summary statistics for equally-weighted hedge fund quarterly flows for each category from 1994 through 2004. Quarterly flows are reported for Combined, Live and Defunct databases. Investor flows into each fund are defined as the percentage change of net assets of the fund (measured in local currency) between the beginning of a quarter and the end of a quarter net of quarterly returns. For each quarter, we first calculate the percentage flows into each hedge fund.

Then, we aggregate them within a category using both equal and asset-weighted methods.[20] We also windsorize the top 1% percentage flows to eliminate outliers.

Hedge funds as a whole enjoy high growth rates in the sample period (Panel A). On average, for each quarter, hedge funds attract flows of 15.93% of total assets at the beginning of the quarter. Using the last available hedge fund asset under management as an asset weight, the asset-weighted flow is 19.84%, showing that hedge funds that have larger asset size on average experience higher percentage flows. For equal weighted flows, this percentage is highest for Multi-Strategy category followed by Global Macro and Fixed Income Arbitrage. On the other end, Managed Futures and Emerging Markets attract the least flows per quarter. Comparing 15.93% to average returns (Table I, after calculating a quarterly return), we see that on average hedge funds grow externally, through an increase in fund flows. However, the growth of fund flows is not smooth, with an average standard deviation of fund flows of 33.96%. Average flows fluctuate from a minimum of -22.77% to a maximum of 92.16%. Equity Market Neutral, Global Macro and Multi-Strategy see high volatility in flows while Emerging Markets, Event Driven and Funds of funds have the lowest volatility in flows; however, for all hedge fund styles the volatility of flows is quite high: fluctuating from 24.41 to 47.72%. It is worth noting that the quarterly flows also exhibit positive skewness and an excess kurtosis of 3.16-4.56; however, the Jarque-Bera test of normality does not reject the normal distribution for all styles in the combined database. Flows also tend to be sticky (serial correlation = 11.50).[21]

[20] AWF is the asset-weighted quarterly fund flow using the last available assets under management for a hedge fund as an asset weight. We also computed, but not tabulated the asset-weighted quarterly fund flow using the average assets under management for a hedge fund as an asset weight over the period of 1994 to 2004.

[21] Specifically, the first order autocorrelation coefficient is much higher for quarterly flows for all hedge fund categories compared to serial correlation in annual flows. Therefore, hedge fund flows are more persistent on quarterly versus annual intervals. Getmansky (2005) found that category hedge fund flows are cyclical with a period of about 1 year. Generally, hedge fund flows are sticky on quarterly basis. Agarwal and Naik (2000b), using two-period and multi-period framework, find that persistence in annual flows is mostly attributable to persistence in losers and not winners.

Panels B and C separate flows into Live and Defunct databases. On average, flows are much higher (asset-weighted, equally-weighted and median) for Live versus Defunct database (i.e., equally weighted flow for Live funds is 20.10% compared to 9.69% for Defunct funds). Also, the Live database has less negative minimum flows (-17.12% compared to -31.24% for the Defunct database) and much higher maximum flows (99.33% compared to 81.43% for the Defunct database), which makes sense as the Defunct database lists liquidated funds.

<Insert Table III >

Parameter statistics for flow restrictions are presented in Table III, Panel A. The median subscription, redemption and advance notice periods are 30 days each. The median lockup period is 0 days, so 50% of hedge funds have no lockup periods and 50% of hedge funds have a lockup period with the maximum lockup period reaching 2,700 days. The median θ_0, asset illiquidity proxy, is 0.86. 38% of all hedge funds are onshore and 29% of all hedge funds are in capacity constrained categories. We borrow the methodology from Getmansky (2005) who concluded that convertible arbitrage, emerging markets, fixed income arbitrage and event driven strategies are capacity constrained, i.e. funds in these categories experience decreasing returns to scale. We use the median values of these restriction parameters to define low restriction and high restriction funds. For example, a fund with a θ_0 equal to or above 0.86 is regarded as a high liquidity fund and a low liquidly fund otherwise.

Note that there is a distinction between share restriction at the fund level and asset illiquidity at the underlying security level.[22] A fund with a lockup provision may not necessarily invest in illiquid securities.[23] However, we do expect, in general, share restriction variables and asset illiquidity

[22] Liang and Park (2007) indicate that onshore funds have more share restrictions but invest in more liquid assets than offshore funds.

[23] For example, some funds extended their lockup periods over two years in order to escape the SEC regulation.

measure are positively correlated. Table III, Panel B presents univariate results for low (low liquidity) and high θ_0 (high liquidity) funds. We find that all restrictions, i.e., subscription, redemption, advance notice, total redemption and lockup periods and capacity constrained restrictions monotonically increase with increase in asset illiquidity, i.e., decrease in θ_0. All the differences in between the two groups are highly significant. Onshore[24] is the only restriction that decreases with asset illiquidity. Onshore funds impose more severe share restrictions than offshore funds on average (Liang and Park, 2007). Also, onshore funds are generally organized as limited partnerships (compared to open ended investment companies for offshore funds) and therefore should have more asset illiquidity than offshore counterparts. However, despite restrictions on the number of hedge fund investors, the minimum wealth required for investors and a ban on advertising imposed by U.S. regulations, U.S.-based funds tend to invest in more liquid assets[25]. Therefore, with the exception of the onshore domicile, all hedge fund share restrictions directly correlate with asset illiquidity. Asset illiquidity measure has to be deduced from the returns data and is not specifically outlined in hedge fund contracts compared to other share restrictions that are clearly spelled out in hedge fund contracts. The fact that the asset illiquidity measure is highly correlated with share restrictions means that hedge fund managers do a good job in aligning asset illiquidity with share restrictions stipulated by investment contracts. In conclusion, asset illiquidity measure, θ_0, is a good proxy for various hedge fund share restrictions[26].

[24] In the TASS database, there is no field for onshore and offshore; however, each hedge fund has a state and a country associated with it. However, some information is missing and is incomplete. Therefore, we identified a country as offshore if it has a missing state. An alternative way is to identify a country if a country has the following codes: "United States," "United Stat," "United St," "United," "United S," "Unit," "United State," "U," "Delaware," "Un," "Unite," "United Sta," and "Uni." As a robustness check, we also ran the models using this specification and obtained similar results.

[25] Getmansky, Lo and Makarov (2004) and Liang and Park (2007) find that U.S. domicile (onshore) is correlated with a high θ_0, more asset liquidity.

[26] For robustness, we have re-run this analysis using autocorrelation in returns, requiring a minimum of 3 years of data. Our results are very similar to the ones obtained by using θ_0 as a proxy for asset illiquidity. Results are not reported, but available upon request.

B. Fund Flow-Performance Relation: All Funds

Fund flow-performance relations are analyzed in Table IV. In analyzing the flow-performance relation, we estimate a piecewise linear regression between current fund flows and past returns--current fund flows are estimated as the percentage change in total net assets, adjusted for investment returns (the methodology used to capture this relationship is described in Section IV.A).

<Insert Table IV >

Table IV shows that the estimates for low performance (0.921), middle performance (0.906) and high performance (0.906) terciles are nearly identical, and all three coefficients are significant at the 1% level. Chow tests do not reject the equality of these three coefficients—therefore, the relationship between flows and past returns is linear for the universe of funds. This result is similar to that of Baquero and Verbeek (2005), who also find a linear fund flow-performance relation.

Other significant variables in the regression are volatility (standard deviation), size, live/defunct dummy, advance notice period, high water mark provision, leverage, subscription period, and the style effect. Highly volatile funds can discourage risk-averse investors to invest in these funds. This explains the negative relation between flow and volatility. Similar to mutual funds, percentage flows are less sensitive to performance for large funds. The Live/defunct dummy clearly captures the difference between flows across the live and defunct groups.

Advance notice period is positively related to flows as funds investing in illiquid securities earn high returns due to liquidity premium (Aragon (2007), Liang and Park (2007)) and may require longer notice period. As a signal, high quality funds may also require longer notice periods than low quality funds. The positive relation between notice and flow is consistent with a positive relation between performance and flows. Funds with a high watermark provision require managers to make up previous losses before claiming profits, hence the presence of high watermark provision serves as a signal to investors about the quality of the funds. Levered funds may not have as large an equity size as unlevered funds, other things fixed; hence the percentage flows are positively related to leverage, which is consistent with the size story. It is also possible it is easier for high quality funds to borrow money than low quality funds, indicating leverage can serve as a signal for fund quality.

Funds with more frequent subscription period (say monthly instead of yearly) will bring money into the fund more frequently. Hence the relation between subscription period and flow is negative[27]. Finally, style effect is positively related to individual fund flows as "hot" styles can certainly attract money flows to those funds within the same style and the individual fund performance can also be highly correlated with the style performance.

C. Restrictions on Fund Flows: Testing Hypotheses 1A and 1B

C.1. Share and Asset Illiquidity Restrictions

This section tests whether share restrictions and asset illiquidity affect the shape of the flow-performance relationship for individual funds through direct (Hypothesis 1A) and/or indirect (Hypothesis 1B) effects.[28] For robustness, we conduct the test in three ways:

First, in Panel A of Table V, we report the result for a single restriction variable, θ_0. According to the results in Table III, Panel B, θ_0 is a good proxy for share restrictions. Therefore, using the same combined sample of hedge funds as in Table IV, we analyze the effect of θ_0 on the flow-performance relation[29].

<Insert Table V >

[27] The subscription period variable is measured as the number of days in-between possible money flows. The larger the number, less frequently the fund takes in money. Hence, a negative coefficient indicates funds that accept money more often attract more flows.

[28] Hypotheses 1A and 1B are not mutually exclusive.

[29] ManagementFee_i, OpentoPublic_i, and LockupPeriod_i are not significant in Table IV; therefore, are omitted in Table V.

Table V, Panel A captures the effect of low θ_0 --low liquidity--on the flow-performance relation by interacting low θ_0 with Low, Middle and High Performance terciles. In the absence of share restrictions implied by low liquidity, the fund flow-performance relation is convex: the estimates on Low, Middle and High Performance terciles are 0.720, 0.786 and 0.870, respectively. All these estimates are significant at the 1% level. The presence of the restriction (Low θ_0 =1) increases the Low Performance estimate by 0.538 and reduces the High Performance estimate by 0.692, both significant at the 1% level. Hence, the presence of the restrictions leads to the following performance tercile estimates: Low (1.258), Middle (0.954) and High (0.178), which clearly represents a concave relationship[30]. As low θ_0 proxies for various share restrictions, the presence of these restrictions leads to the concave fund flow-performance relationship, which is consistent with Prediction 1. Specifically, in the low-performance region, investors can easily anticipate restrictions, as lock-up provisions, advance notice periods, and redemption periods are directly observable and clearly specified in investment contracts. Therefore, in this region, investors endogenize these restrictions (Hypothesis 1B), which are more relevant for low-performance regions. Once hedge funds achieve high returns, hedge fund managers are more likely to close their funds to new investors or reduce the inflow of new capital due to capacity constraints. Since these restrictions are not clearly outlined in investment contracts, investors are less likely to anticipate the managers' decisions. Therefore, the direct effect dominates in the high-performance region in the presence of restrictions (Hypothesis 1A). Taken together, the presence of restrictions leads to a concave fund flow-performance relation, which is consistent with Prediction 1.

[30] Autocorrelation and Ψ results are consistent with θ_0 results, where $\Psi = \theta_0^2 + \theta_1^2 + \theta_2^2$ (Getmansky, Makarov and Lo (2004). Results are not reported, but available upon request.

Second, Panel B of Table V analyzes the joint impact of two share restrictions on fund flow-performance relationship. The impact of outflow restriction: total redemption period and inflow restriction: capacity constrained styles are presented. The interaction terms of Low Performance tercile with Long Total Redemption and Capacity Constrained are 0.598 (significant at the 10% level) and 0.498 (significant at the 5% level), respectively. The interaction terms of High Performance tercile with Long Total Redemption and Capacity Constrained are 0.179 (insignificant though) and -0.735 (significant at 5% level), respectively. Therefore, in the presence of these two restrictions, the estimates on Low, Middle and High Performance terciles are 1.651, 0.384, and 0.196 respectively. This is, again, consistent with Prediction 1 that the presence of restrictions leads to a concave fund flow-performance curve.

Finally, the presence of all restrictions (subscription period, onshore/offshore, capacity constrained styles, total redemption period, asset illiquidity and lockup provision restrictions) is analyzed in Table V, Panel C. Consistent with Prediction 1, the interaction between the Low Performance and the sum of all these six restrictions is 1.064, between the Middle Performance and the sum of all six restriction is -0.640 and between the High Performance and the sum of all six restrictions is -0.514[31]. Therefore, in the absence of all restrictions, the fund flow-performance relationship is convex (0.713, 0.891, and 1.097 for Low, Middle and High performance terciles). In the presence of all six share and asset illiquidity restrictions, the fund flow-performance becomes concave (1.777, 0.251, and 0.583 for Low, Middle and High performance terciles). Overall, the presence of restrictions increases the estimated sensitivity of the low performance tercile (due to outflow restrictions) and decreases the estimated sensitivity of the high performance tercile (due to inflow restrictions). This evidence is consistent with Prediction 1.

[31] Individual restriction interactions are all in the right direction, except the onshore domicile proxy.

C.2. Style Analysis for Capacity Constraint

To further examine the impact of the capacity constraint on the flow-performance relation, we conduct a style analysis. Specifically, we pick two styles: long/short equity and fund of funds that are less likely to be capacity constrained compared to other arbitrage styles. Both have a large enough number of funds which allows us to conduct this analysis by style. Table VI Panel A displays the results for the flow-performance relation for long/short equity hedge funds for which we have the largest number of observations out of all 11 styles. Interestingly, the flow-performance relations are all convex for combined, live, and defunct groups, although the Chow tests did not indicate any significant differences across the three flow-performance coefficients. For the long/short equity hedge funds, the best performing funds attract the most money flows. This is true for combined, live, and defunct funds. This is also consistent with Prediction 2: less constrained style like long/short equity[32] displays a convex flow-performance relation.

<Insert Table VI>

In addition to long/short equity hedge, fund of funds is another category that we have a sufficient number of observations for a meaningful analysis.[33] The flow-performance relation for fund of funds is reported in Table VI, Panel B. Again, the flow-performance relations are convex for combined and live funds, but only one out of three coefficients for the combined group is significant at the 10% level. Chow tests indicate the slope for the high performance group is different (at the 1% level) from the other two groups for the combined dataset, while, for the defunct dataset, it is statistically different at the 10% level. Again, this convex relation is consistent with Hypothesis 1. Unlike hedge funds, fund of fund managers rely heavily on management fees and have no incentive to impose a capacity restriction for their funds. In addition, some well-performing

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[32] Unlike some arbitrage styles such as convertible arbitrage or fixed income arbitrage, long/short equity has less capacity constraint. However, we do not have enough funds to conduct a separate analysis for the arbitrage styles.

[33] Other 9 styles do not have enough annual observations for us to perform similar analysis.

funds are closed to individual investors but are still open to funds of funds. As a result, investors can access these funds through funds of funds.

In summary, conducting a style analysis, we find that (consistent with Prediction 2) the most unconstrained styles such as Long/Short and Fund of Funds exhibit an increased sensitivity in the high-performance region, and, thus, a convex flow-performance relation.

D. Heterogeneity of Fund Flow-Performance Relationship, Live vs. Defunct: Testing Hypothesis 2

Hedge funds that have higher returns may experience higher net flows. Agarwal, Daniel, and Naik (2004) find a convex relationship in hedge fund flow-performance relationship. Getmansky (2005) finds a concave relationship in hedge fund flow-performance relationship and Baquero and Verbeek (2005) find a linear fund flow-performance relationship. These results depend on the database used, time period analyzed, and frequency of the sample. However, all these studies assume homogeneity of the fund flow-performance relationship across hedge funds, and do not explicitly take into consideration the impact of various restrictions on this relationship, especially the impact of survivorship bias. Previous studies (Fung and Hsieh (2000) and Liang (2000)) find defunct funds have a large impact on performance. Therefore, to examine the flow-performance relation, we must consider live funds as well defunct funds. Unlike previous studies in fund flows, we conduct the analysis on both Live and Graveyard databases and separate the analyses for different hedge fund strategies.

Table VII reports the results for flow-performance relation for combined, live, and defunct funds after controlling for fund characteristics. As reported in table IV, for the combined database, the coefficients for the three performance ranks are all positive at 0.92, 0.91, and 0.91 for the low, middle, and high performance groups, respectively, indicating a linear flow-performance relation.

However, when we split the combined sample into live versus defunct funds, we clearly see the difference in these coefficients. For the live funds, the high performance group has the lowest coefficient (0.707) while the coefficient (1.203) is the highest for the defunct funds. In other words, the flow-performance relation is concave for live funds but convex for the defunct funds.[34] As a result, the aggregate result for all funds combined is a flat relation. This can be seen clearly in Figure 1. Note that in Figure 1, the slope coefficient for defunct funds exceeds that of live funds at the high performance region, indicating the best performed defunct funds may attract more flows than the live ones (we will discuss this later). Effectively, through splitting the data into live and defunct, our paper contributes to the hedge fund flow literature by reconciling the conflict results by previous authors who pool the data together and may not reveal the true flow-performance relation.

< Insert Table VII, Figure 1>

In line with Hypothesis 2, we conjecture that the concave relation for live funds in the hedge fund database is due to better performing funds' voluntary closure to new investment while the convex relation for defunct funds is due to the divergent reasons why a fund drops out of the database (Chan, Getmansky, Hass, and Lo, 2005). Specifically, better performing funds in the Live database might decide to close after facing diminishing returns to scale due to capacity constraints. Due to capacity constraints, top funds in this industry choose not to grow too quickly in order not to face diminishing returns (Berk and Green, 2004). Hedge fund managers make money both on management and incentive fees[35]. Therefore, to optimize incentive fees, hedge funds might choose not to attract as much flows when facing capacity constraints, increase in assets under management

[34] Although the Chow test did not show statistical significance, the differences are economically important.

[35] The relative break-down between management and incentive fees depends on the age of the fund and total assets under management. Christoffersen and Rouah (2007) argue that when CTAs are small and young, they take higher risk and heavily rely on incentive fees while they take less risk and rely on management fees when they are large and old.

and returns[36]. Moreover, hedge funds sometimes operate in illiquid markets, thus a disproportional increase in flows will lead to a disproportional increase in market impact, reducing opportunities and incentive fees even further. Funds get into the defunct database due to two different reasons. Specifically, the best-performing funds chose not to attract any more capital by being listed in the database, while worst-performing funds are liquidated.

The conjecture that the concave relation for live funds is due to better-performed funds' voluntary closure to new investment is tested and results are reported in Table VIII. Table VIII reports the percentage of funds closed to new investment, average performance rank and monthly returns for the three performance groups: Low, Middle and High. Since we are interested in the relationship between voluntary closure to new investment and the high performance group, we combine low and middle performance groups. Note that we use two different versions of TASS data (January 2001 and September 2005) in order to capture the different dynamics between fund closure, performance, and ranks over time.[37] January 2001 (Panel A)/ September 2005 (Panel B) TASS versions include hedge funds that are opened or closed to new investment as of January 2001 and September 2005 respectively. In Panel A, the percentage differences between the high performance and low/middle performance groups are basically positive for all years until 2000[38] when January 2001 data shows the closure; these differences remains negative for the remaining years when funds remain closed to new investment. In Panel B, since the closure happened at or before 2005, all the differences between the high and other performance groups in terms of the percentage of funds being closed, ranks, and returns are basically positive from 1993 to 2003 showing that hedge funds that are in the high performance rank are more likely to close. Table VIII

[36] Getmansky (2006) find that funds that face capacity constraints have optimal assets under management.
[37] Ideally, we will have a time series of an Open to Investment variable (OpenToInv) to capture the relationship between open to investment and fund performance. However, we are limited by a static OpenToInv variable available in the database. Tremont Company updates any changes to the OpenToInv variables in new versions of the TASS database.
[38] TASS may not update this data field often hence there could be a lag between fund's reporting date to TASS and the actual closing date.

confirms our conjecture: the high performance group has the highest percentage of funds being closed to new investment, resulting in reduction in money flows and a concave flow-performance relation across performance ranks.

< Insert Table VIII>

We furthermore conjecture that the convex relation for defunct funds is due to the different reasons why a fund drops out of the database[39]. In particular, defunct funds are not equivalent to dead funds. In Table IX, we tabulate the distribution of drop reasons out of the TASS data across the three performance groups. Assuming that liquidated funds are poorly performing funds, we observe a higher percentage (52%) of funds being liquidated in the low and middle performance groups than that in the high performance group (46%). In contrast, the percentage of funds voluntarily stopping reporting to TASS is the highest (36%) for the best performing funds, while it is lowest (29%) for the worst performing funds. The Chow test shows, for liquidated funds, the percentage for the high performance group is significantly different than percentage for middle/low performance group at the 10% level. For funds that voluntarily stopped reporting, the percentage for the high performance group is significantly different than percentage for the low performance group at the 10% level and for middle performance group at the 12.5% level.

Funds report to data vendors voluntarily for the purpose of indirect marketing to potential investors.[40] When a fund performs well and has large capital flows, it may have no incentive to continue reporting to the data vendor. As a result, the best performing funds in the defunct group are not "dead" funds; they choose to withdraw from the data vendor. These funds grow proportionally more than liquidated funds (even more than the best-performed live funds) as these funds have better reputation and are more likely to be above the hurdle rate. As a result, voluntary

[39] Chan, Getmansky, Hass and Lo (2006) and Liang and Park (2007) show that worse performing and dead funds are more likely to be located in the "liquidated" versus "no longer reporting category."
[40] Hedge funds are not allowed to conduct direct public advertisement. Reporting to data vendors can lead to potential investors being interested in investing in the fund.

withdrawal is a strong signal for quality. The above results on the distribution of different drop reasons can explain the convex flow-performance relation for the defunct funds.

< Insert Table IX>

In summary, live funds that have performed well might decide to be closed to new investment due to capacity constraints, thus imposing investment restrictions. This leads to a reduced sensitivity in the high-performance region and subsequently a concave fund flow-performance profile. A hedge fund has two main reasons to be in the defunct database: (1) liquidation due to prior poor performance or (2) exceptionally good performance and a subsequent decision to withdraw from the data vendor. In this set-up, these good performing funds command disproportionate fund flows (i.e., steeper fund flow-performance slope), compared to liquidated counterparts. Therefore, for defunct funds, we find a convex fund flow-performance relationship[41].

E. Smart Money Effect and the Effect of Flow Restrictions on the Performance of Flows: Testing Hypothesis 3

Is money "smart" in hedge fund markets? Can investor flows predict future hedge fund returns? Past research by Zheng (1999) finds evidence that flows into mutual funds earn positive risk-adjusted returns. However, Wermers (2004) and Sapp and Tiwari (2004) ascribe the smart money to funds investing the inflows in the winning stocks which generate short-term abnormal return. In the hedge fund arena, Agarwal, Daniel, and Naik (2004) find that the annual hedge fund return is negatively related to the fraction flows in the prior year. Baquero and Verbeek (2005) find that the new flows can deliver outperformance, but for only one quarter. In this section, we examine the performance of hedge fund flows to determine whether investors have selectivity in

[41] Getmansky, Lo and Makarov (2004) found that on average, live funds have higher illiquidity (mean θ_0 =0.891) compared to defunct funds (mean θ_0 =1.001).

picking hedge funds and if share restrictions have an impact on the smart money effect. This analysis can also help to uncover whether fund flows impact markets in which the funds invest.

We measure the performance of portfolios of hedge funds using the performance measure of Grinblatt and Titman (1993), as shown by equation (5). That is, prior-quarter weights on each hedge fund are subtracted from current-quarter weights, and this weight difference is multiplied by the following quarter hedge fund return. Then, these differenced-weight return components are summed to arrive at the *GT* measure for a particular category. If money moves into funds with higher future returns and comes out from funds with lower future returns, then the *GT* measure will indicate positive performance.

<Insert Table X >

In Table X, we report the time-series average of this *GT* measure as well as flows-weighted zero-cost portfolio return and equally-weighted zero-cost portfolio return.[42] The zero-cost portfolios are generated at the beginning of each quarter with long position in funds with positive flows during the past quarter, and short position in funds with negative flows. If investors have ability in picking funds, or their flows impact asset returns, then we expect to see that these three performance measures are significantly positive.

The results show evidence of positive performance for flows. In fact, none of the performance measures are (significantly) negative for any category of funds, including the combined sample for all funds. For instance, the *GT* measure for flows into all funds is 0.35%, which is significant, indicating that investors smartly allocate money to future high performers and withdraw money from future losers. Further results show that flows to fixed income arbitrage, long/short

[42] The zero-cost portfolios are generated at the beginning of each quarter from 1994 through 2004. Specifically, at the beginning of each quarter, we put each hedge fund into a positive-flows (negative-flows) fund portfolio if the prior-quarter flows are positive (negative). Then a flows-weighted (equally-weighted) zero-cost fund portfolio is formed by going long on the positive-flows fund portfolio weighted by flows (equally) and going short on the negative-flows fund portfolio weighted by flows (equally).

equity hedge, and multi-strategy achieve a positive and significant *GT* measure of performance. For example, the flows to long/short equity hedge funds earn an annualized return of 4.88% during the following quarter, with a flows-weighted portfolio, and 2.34% with an equally-weighted portfolio.

We test Hypothesis 3 by investigating whether restrictions affect the "smart money" result. Specifically, we try to understand whether the "smart money" effect is reduced by share restrictions and asset illiquidity. We run a multi-factor model to explain the return of a zero-cost equal-weighted portfolio of hedge funds with positive flows in the prior quarter and short hedge funds with negative flows in the prior quarter.[43] Although the use of this model cannot directly test whether flows can predict future hedge fund returns, it can shed light on if investors possess fund selection skill and how hedge fund managers incorporate investment flows. The regression results are presented in Table XI.

<Insert Table XI >

We find that the zero-cost portfolio earns a positive monthly alpha of 1.62% after controlling for the market indexes and factors.[44] The alpha is higher than the time-series average of quarterly raw returns as reported in Table X and consistent in magnitude with Aragon (2007) that share restrictions imposed by hedge funds allow hedge fund managers to earn a liquidity premium of 4-7% a year. Further, Table XI shows that the outperformance of flows into hedge funds is partially due to the size factor (LMS) and the momentum factor (UMD), two well-known equity market factors, consistent with the notion that taking long (short) position of small-cap winning (losing) stocks is a common practice conducted by long/short equity funds. On the other hand, the performance of flows is significantly negatively related to the performance of other asset classes such as fixed income securities, LIBOR, US dollar, and gold, indicating that investors of long/short equity hedge funds focus on the investment opportunity in the equity market.

[43] Long/Short Equity hedge funds have the largest number of funds out of all hedge fund styles.
[44] The alpha is significant at the 5% level.

To test Hypothesis 3, that is whether and how share restrictions directly affect the smart money effect, we further divide the hedge funds based on their θ_0.[45] We run the same multi-factor model for two subsets of the dataset: hedge funds with low restrictions (High θ_0 funds) and hedge funds with high restrictions (Low θ_0 funds). We find that the presence of restrictions clearly reduces the smart money effect, i.e., in the absence of restrictions the monthly alpha is 2.08% (t-stat 2.46); however, in the presence of restrictions, the alpha drops to 1.12%, and is insignificant from zero.. We further run the Chow test to test whether the regression coefficients are equal. The *F*-statistic is significant at the 5% level, which means that the restrictions have significant impact on the performance of flows. In conclusion, we find evidence that the smart money effect is reduced by share restrictions, which is consistent with Hypothesis 3.

Overall, we find a strong evidence for the effect of restrictions on smart money. The presence of restrictions clearly reduces the smart money effect.

VI. Conclusion

In this paper, we analyze the impact of restrictive features of individual hedge funds on the fund flow-performance relation. We find that share restrictions such as subscription, advance notice, redemption and lockup periods, capacity constraints, a limit on the number of allowed investors, and asset illiquidity generally lead to a concave fund flow-performance relation by limiting fund withdrawals that generally affect low-performing funds and reducing the responsiveness of flows to increased performance among higher-performing hedge funds. Moreover, we also find that asset illiquidity proxy (θ_0) is a good proxy for all share restrictions, except onshore domicile. The concave relation we found forms a strong contrast with the mutual fund literature where the flow-

[45] As shown in Table III, θ_0 is a good proxy for share restrictions.

performance relation is convex when no share restrictions exist, and is consistent with investors endogenizing restrictions in their investment decision.

We also find that the flow-performance relation is substantially different for live and defunct funds. For live funds, the relation is concave: better performing funds have a lower flow sensitivity to past performance than worse-performing funds—consistent with better performers more frequently (1) closing to new investments, or (2) discontinuing their disclosure in public databases than other funds (thus, moving them to the defunct database). In contrast, defunct funds show a convex flow-performance relation due to poorly performing funds becoming liquidated as well as to better-performing funds that have discontinued disclosure being moved to this database.

By considering share restrictions and asset illiquidity as well as treating live and defunct funds separately, we effectively reconcile the conflicting results from previous studies where the flow-performance relations are concave, convex, and linear.

Finally, we examine whether investor flows are "smart," that is, whether inflows predict individual hedge fund outperformance, while outflows predict underperformance. Generally, we find evidence that flows predict performance. We further test whether share restrictions and asset illiquidity reduce the "smart money" effect. We find evidence that the "smart money" effect is reduced by these restrictions. Specifically, in the absence of restrictions (High θ_0 funds), investors can successfully withdraw funds from future losers; however, the presence of restrictions (Low θ_0 funds) results in a decreased "smart money" effect.

Future research may use our results to study the behavior of flows at the style or macro level. Such research may provide insight into whether hedge fund investment activity, partly driven by flows, may exacerbate or mitigate contagion in financial markets. We are currently expanding our research in these directions.

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Table I Summary Statistics of Hedge Fund Returns by Category: 1994Q1-2004Q4

In this table we report the descriptive statistics of monthly returns for each category from 1994 through 2004. Panel A, Panel B and Panel C show statistics for monthly combined, live and graveyard hedge fund returns, respectively. Returns are equally-weighted for all funds in a category. We report the mean (EWR), median, maximum, minimum, standard deviation, skewness, kurtosis and first order autocorrelation coefficient of reported returns for each category as well as for all categories except Fund of Funds. We also report mean asset-weighted returns AWR. AWR is the asset-weighted return using the last available dollar assets under management for a hedge fund as an asset weight. All numbers except skewness and kurtosis are in percent. We also report the number of hedge funds in each category. Median Jarque-Bera normality statistics (JB-Stat) are reported for each category. *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level.

Panel A: All Funds

	N	AWR (%)	EWR (%)	Median (%)	Stdev (%)	Min (%)	Max (%)	Skew	Kurt	ρ_1 (%)	*JB*-Stat
All (except Fund of Funds)	3448	1.15	0.87	0.74	4.27	-9.57	12.30	0.09	2.53	0.10	3.10
Convertible Arbitrage Convertible	166	0.90	0.66	0.72	1.84	-4.18	4.97	-0.20	1.87	0.32	1.89
Dedicated Short Bias	30	0.42	-0.16	-0.40	6.37	-16.24	17.79	0.22	1.55	0.04	1.68
Emerging Markets	257	1.49	1.03	0.98	6.71	-18.03	19.17	-0.20	3.73	0.16	6.94**
Equity Market Neutral	238	0.80	0.60	0.53	2.39	-4.71	6.91	0.12	1.74	0.03	1.73
Event Driven	378	1.16	0.99	0.91	2.36	-5.20	6.99	-0.03	2.63	0.19	5.37*
Fixed Income Arbitrage	184	0.85	0.69	0.81	1.94	-6.38	4.85	-0.88	7.14	0.15	5.69*
Global Macro	215	1.09	0.69	0.56	4.25	-8.96	11.87	0.27	2.07	0.03	3.20
Long/Short Equity Hedge	1371	1.30	1.06	0.87	4.84	-10.33	14.30	0.26	2.16	0.09	2.76
Managed Futures	467	1.07	0.53	0.27	5.75	-12.67	15.95	0.18	1.73	0.00	2.77
Multi-Strategy	142	1.15	0.90	0.76	3.20	-6.44	9.44	0.09	3.41	0.14	3.41
Fund of Funds	996	0.73	0.61	0.54	2.22	-4.77	6.44	-0.08	2.16	0.23	1.54

Panel B: Live Funds

	N	AWR (%)	EWR (%)	Median (%)	Stdev (%)	Min (%)	Max (%)	Skew	Kurt	ρ_1 (%)	*JB*-Stat
All (except Fund of Funds)	2068	1.17	1.10	0.94	3.51	-7.57	10.96	0.18	2.47	0.13	2.85
Convertible A	107	0.89	0.78	0.80	1.55	-3.18	4.87	-0.11	1.10	0.34	2.13
Dedicated Short Bias	16	0.32	-0.46	-0.75	6.48	-17.60	16.52	0.15	1.53	0.01	1.96
Emerging Markets	137	1.60	1.66	1.53	5.85	-16.35	20.12	-0.04	4.07	0.19	10.20***
Equity Market Neutral	146	0.79	0.59	0.56	1.89	-3.84	5.69	0.15	1.80	0.02	1.68
Event Driven	263	1.18	1.17	1.01	2.05	-3.88	6.66	0.19	2.35	0.21	5.35*
Fixed Income Arbitrage	120	0.88	0.82	0.86	1.55	-4.72	4.29	-0.70	6.33	0.15	3.73
Global Macro	111	1.10	0.95	0.80	3.50	-6.93	10.18	0.30	1.84	0.03	3.03
Long/Short Equity Hedge	876	1.30	1.23	1.03	3.99	-8.19	12.71	0.36	2.19	0.11	2.44
Managed Futures	188	1.11	0.96	0.66	5.40	-11.56	15.48	0.19	1.45	0.02	1.88
Multi-Strategy	104	1.16	1.11	1.00	2.72	-5.23	8.16	0.14	3.62	0.18	4.41
Fund of Funds	739	0.74	0.70	0.62	1.76	-3.35	5.66	0.00	2.02	0.26	1.25

Panel C: Defunct Funds

	N	AWR (%)	EWR (%)	Median (%)	Stdev (%)	Min (%)	Max (%)	Skew	Kurt	ρ_1 (%)	*JB*-Stat
All (except Fund of Funds)	1380	1.01	0.53	0.42	5.42	-12.56	14.31	-0.06	2.63	0.07	3.53
Convertible arbitrage	59	0.93	0.44	0.59	2.36	-6.00	5.16	-0.35	3.26	0.28	1.60
Dedicated Short Bias	14	0.62	0.17	0.00	6.25	-14.69	19.25	0.29	1.58	0.07	1.67
Emerging Markets	120	0.70	0.32	0.36	7.69	-19.94	18.08	-0.38	3.34	0.12	3.64
Equity Market Neutral	92	0.85	0.61	0.49	3.18	-6.10	8.85	0.07	1.63	0.03	1.77
Event Driven	115	0.98	0.58	0.70	3.08	-8.23	7.75	-0.53	3.26	0.14	5.62*
Fixed Income Arbitrage	64	0.65	0.44	0.70	2.66	-9.50	5.91	-1.23	8.66	0.14	33.97***
Global Macro	104	1.05	0.42	0.31	5.06	-11.13	13.66	0.24	2.31	0.03	3.62
Long/Short Equity Hedge	495	1.28	0.77	0.60	6.35	-14.13	17.12	0.09	2.12	0.06	3.18
Managed Futures	279	0.68	0.24	0.01	5.99	-13.42	16.27	0.17	1.92	-0.01	3.58
Multi-Strategy	38	0.94	0.31	0.13	4.51	-9.77	12.95	-0.07	2.84	0.04	1.90
Fund of Funds	257	0.69	0.35	0.29	3.54	-8.83	8.70	-0.32	2.56	0.13	2.85

Table II Summary Statistics of Hedge Fund Quarterly Flows by Category: 1994Q1-2004Q4

In this table we report the descriptive statistics of quarterly flows into hedge funds by category from 1994 through 2004. Investor flows into each fund are defined as the percentage change of net assets of the fund (in local currency) between the beginning of a quarter and the end of a quarter net of quarterly returns. For each quarter, we calculate the percentage flows into each hedge fund. When aggregating the flows within a category, we windsorize the top 1% percentage flows. Panel A, Panel B and Panel C show statistics for quarterly combined, live and graveyard hedge fund flows, respectively. Flows are equally-weighted for all funds in a category. We report the mean (EWF), median, maximum, minimum, standard deviation, skewness, kurtosis and first order autocorrelation coefficient of fund flows for each category as well as for all categories except Fund of Funds. We also report mean asset-weighted flows AWF. AWF is the asset-weighted flow using the last available dollar assets under management for a hedge fund as an asset weight. All numbers except skewness and kurtosis are in percent. We also report the number of hedge funds in each category. Median Jarque-Bera normality statistics (*JB*-Stat) are reported for each category. *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level.

Panel A: All Funds

	N	AWF (%)	EWF (%)	Median (%)	Stdev (%)	Min (%)	Max (%)	Skew	Kurt	ρ_1 (%)	*JB*-Stat
All (except Fund of Funds)	3448	19.84	15.93	8.40	33.96	-22.77	92.16	0.99	4.01	11.50	2.76
Convertible Arbitrage	166	23.09	14.67	7.55	33.59	-24.05	95.36	1.10	3.22	10.93	2.09
Dedicated Short Bias	30	6.77	11.30	4.05	34.20	-29.68	79.52	0.86	3.16	12.49	2.58
Emerging Markets	257	12.47	9.68	5.14	24.41	-23.40	67.59	0.92	4.56	10.99	4.13
Equity Market Neutral	238	18.21	18.99	9.90	39.42	-25.09	100.62	0.94	3.42	13.34	1.31
Event Driven	378	19.92	17.27	10.86	29.21	-16.07	80.97	0.94	3.38	13.09	2.43
Fixed Income Arbitrage	184	23.84	20.05	12.22	33.73	-17.92	98.46	1.19	3.93	12.12	2.17
Global Macro	215	25.14	20.79	11.49	42.36	-25.21	109.70	0.84	3.90	8.62	2.16
Long/Short Equity Hedge	1371	19.08	15.84	8.00	33.27	-21.42	91.38	1.07	4.10	12.76	2.90
Managed Futures	467	16.42	9.59	3.29	34.53	-33.22	90.37	0.80	4.55	7.66	4.00
Multi-Strategy	142	20.84	30.10	18.09	47.72	-13.89	130.00	1.10	4.32	10.42	3.21
Fund of Funds	996	17.61	14.62	8.29	28.25	-16.57	74.76	0.97	3.85	9.93	2.55

Panel B: Live Funds

	N	AWF (%)	EWF (%)	Median (%)	Stdev (%)	Min (%)	Max (%)	Skew	Kurt	ρ_1 (%)	*JB*-Stat
All (except Fund of Funds)	2068	20.51	20.10	11.82	34.55	-17.12	99.33	1.20	4.40	13.25	3.27
Convertible Arbitrage	107	23.59	17.59	9.24	35.58	-22.40	107.49	1.33	3.69	13.11	2.61
Dedicated Short Bias	16	7.41	19.38	8.97	43.42	-24.01	98.92	1.10	2.94	8.56	0.96
Emerging Markets	137	13.00	13.64	8.73	24.06	-18.14	75.48	1.21	6.09	12.93	9.22***
Equity Market Neutral	146	18.04	20.35	10.71	38.40	-20.30	104.12	1.21	3.66	16.43	1.50
Event Driven	263	20.76	20.34	13.69	29.13	-11.64	83.38	1.02	3.40	15.31	2.04
Fixed Income Arbitrage	120	25.07	26.47	17.50	36.08	-11.88	108.87	1.32	4.07	12.34	2.11
Global Macro	111	31.51	30.43	20.75	45.94	-18.12	124.18	1.11	4.24	11.98	2.00
Long/Short Equity Hedge	876	18.96	18.29	10.03	33.36	-17.37	96.54	1.22	4.51	12.88	3.58
Managed Futures	188	17.03	16.27	7.95	35.49	-23.89	102.15	1.25	5.04	13.90	5.86**
Multi-Strategy	104	20.66	34.10	21.90	49.13	-9.29	136.81	1.25	4.92	8.83	4.84*
Fund of Funds	739	18.34	18.26	11.08	29.72	-12.56	80.27	1.13	3.84	10.33	2.28

Panel C: Defunct Funds

	N	AWF (%)	EWF (%)	Median (%)	Stdev (%)	Min (%)	Max (%)	Skew	Kurt	ρ_1 (%)	*JB*-Stat
All (except Fund of Funds)	1380	15.67	9.69	3.26	33.09	-31.24	81.43	0.69	3.49	9.00	2.35
Convertible Arbitrage	59	22.02	9.37	4.47	29.97	-27.04	73.36	0.70	2.40	6.49	1.33
Dedicated Short Bias	14	5.60	2.06	-1.57	24.32	-36.17	57.36	0.59	3.36	15.11	5.30*
Emerging Markets	120	8.81	5.15	1.05	24.81	-29.41	58.58	0.61	2.93	8.78	1.94
Equity Market Neutral	92	19.04	16.83	8.62	41.02	-32.70	95.07	0.55	3.07	8.66	1.30
Event Driven	115	12.18	10.24	4.39	29.39	-26.19	75.44	0.77	3.34	8.60	3.29
Fixed Income Arbitrage	64	16.44	8.03	2.31	29.46	-29.26	78.94	0.96	3.69	11.73	2.80
Global Macro	104	3.09	10.50	1.61	38.58	-32.79	94.24	0.58	3.59	5.41	2.19
Long/Short Equity Hedge	495	19.88	11.51	4.42	33.12	-28.59	82.23	0.81	3.42	12.56	2.34
Managed Futures	279	10.97	5.09	0.16	33.90	-39.50	82.44	0.52	4.25	3.59	3.07
Multi-Strategy	38	24.81	19.17	7.67	44.04	-26.48	111.36	0.72	2.95	14.38	1.23
Fund of Funds	257	10.46	4.14	0.26	24.11	-28.11	58.94	0.56	3.89	8.89	3.31

Table III Restriction Parameters

Panel A reports statistics for different restriction parameters for all hedge funds (not including funds of funds). Lockup, redemption, advance notice, total redemption and subscription periods are reported in days. Total redemption period is the sum of redemption and advance notice periods. θ_0 an asset liquidity measure. Statistics for onshore and capacity dummies are reported. Onshore = 1 if funds reported United States as a domicile country and 0 otherwise. Funds are capacity constrained (capacity constrained = 1) if they belong to emerging market, fixed income arbitrage, event driven and convertible arbitrage strategies. N is the number of hedge funds for which each restriction is available. Panel B reports univariate results for low and high θ_0 funds. This table reports the number of observations, mean and median for different share restrictions for two groups: low and high θ_0 funds. The following share restrictions are considered: subscription period, redemption period, advance notice period, total redemption period, lockup period, onshore and capacity constrained classifications. The difference in means between the two groups and corresponding p-values are reported. *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level.

Panel A: Summary Statistics

	N	Mean	Median	Stdev	Min	Max
Subscription Period	3290	40.61	30.00	35.75	1.00	360.00
Redemption Period	3314	81.71	30.00	80.56	1.00	360.00
Advance Notice Period	3435	29.08	30.00	25.69	0.00	180.00
Total Redemption Period	3310	111.86	60.00	93.81	1.00	540.00
Lockup Period	3425	90.99	0.00	174.42	0.00	2700.00
Onshore	3448	0.38	0.00	0.48	0.00	1
Capacity Constrained	3448	0.29	0.00	0.45	0.00	1
θ_0	950	0.90	0.86	0.23	0.44	2.89

Panel B: θ_0 As a Proxy for Share Restrictions

	Low θ_0 Funds			High θ_0 Funds				
	N	Mean	Median	N	Mean	Median	Diff	p-value
Subscription Period	460	47.16	30.00	434	42.04	30.00	5.12	0.047**
Redemption Period	462	99.06	120.00	444	78.65	30.00	20.59	0.000***
Advance Notice Period	474	35.10	30.00	475	23.37	20.00	11.73	0.000***
Total Redemption Period	462	134.87	137.50	444	103.58	60.00	31.29	0.000***
Lockup Period	471	2.91	0.00	474	2.28	0.00	0.63	0.078*
Onshore	475	0.37	0.00	475	0.45	1.00	-0.08	0.018**
Capacity Constrained	475	0.40	0.00	475	0.18	0.00	0.22	0.000***

Table IV Fund Flow-Performance Relation: All Funds

This table reports Fama-MacBeth OLS estimates with net flow as a dependent variable for all funds in the Combined database. This table presents annual results using the Tremont TASS database covering the period of January 1994 to December 2004. Net flows into each fund are defined as the percentage change of net assets of the fund between the beginning of a year and the end of a year net of yearly returns. The dependent variables are three terciles of performance (Low Performance $_{t-1}$, Middle Performance $_{t-1}$ and High Performance $_{t-1}$) at time t-1, standard deviation of returns at time t-1, natural logarithm of hedge fund dollar assets at time t-1, Live Dummy (1 if a fund is in the live database and 0 if a fund is defunct), Advance Notice Period (measured in days), Open to Public dummy (1 if a fund is open to public and 0 otherwise), High Water Mark dummy (1 if a high water market provision is present and 0 otherwise), Leverage dummy (1 if a fund uses leverage and 0 otherwise), Management Fee (measured as a percentage of assets under management), Incentive Fee (measured as a percentage of a fund's upside above a specific threshold), Lockup Period (measured in days), Redemption Period (measured in days), Subscription Period (measured in days) and Style Effect $_t$ (measured as the average flow for a particular category at time t). *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level.

	All Funds	
Variable	Estimate	*t*-value
Intercept	2.280	5.44***
Low Performance$_{t-1}$	0.921	5.33***
Middle Performance $_{t-1}$	0.906	6.36***
High Performance $_{t-1}$	0.906	4.00***
Standard Deviation $_{t-1}$	-0.020	-3.08**
Log (Size) $_{t-1}$	-0.170	-8.00***
Live	0.243	4.69***
Advance Notice Period	0.001	2.03*
Open to Public	0.090	1.18
High Water Mark	0.126	3.67***
Leverage	0.083	3.15***
Management Fee	-0.021	-0.77
Incentive Fee	-0.002	-0.71
Lockup Period	0.001	0.22
Redemption Period	0.000	-0.44
Subscription Period	-0.001	-3.02**
Style Effect $_t$	0.522	8.34***
Average Number of Observations	692	
Adjusted *R*-squared	13.38%	

Table V Effect of Share Restrictions and Illiquidity on Fund Flow – Performance Relationship

Panel A reports Fama-MacBeth OLS estimates with net flow as a dependent variable for illiquidity θ_0 restriction. The illiquidity θ_0 restriction is interacted with low performance, middle performance and high performance terciles. Panel B reports Fama-MacBeth OLS estimates with net flow as a dependent variable for total redemption period (redemption plus advance notice periods) and capacity constrained restrictions. Fixed income arbitrage, event driven, emerging markets and convertible arbitrage strategies are capacity restricted styles. The long total redemption period and capacity constrained restrictions are interacted with low performance, middle performance and high performance terciles. Panel C reports Fama-MacBeth OLS estimates with net flow as a dependent variable for a unified model that encompasses all six restrictions (subscription period, onshore/offshore, capacity constrained styles, total redemption period (redemption plus advance notice period), asset illiquidity (low θ_0) and lockup provision restrictions). Each individual restriction is interacted with all performance terciles (low, middle and high performance). The summation of interactions for each performance tercile is presented. This table presents annual results using the Tremont TASS database covering the period of January 1994 to December 2004. Net flows into each fund are defined as the percentage change of net assets of the fund between the beginning of a year and the end of a year net of yearly returns. The dependent variables are three terciles of performance (Low Performance $_{t-1}$, Middle Performance $_{t-1}$ and High Performance $_{t-1}$) at time t-1, interaction terms with Low, Middle and High performance terciles, standard deviation of returns at time t-1, natural logarithm of hedge fund dollar assets at time t-1, Live Dummy (1 if a fund is in the live database and 0 if a fund is defunct), High Water Mark dummy (1 if a high water market provision is present and 0 otherwise), Leverage dummy (1 if a fund uses leverage and 0 otherwise), Incentive Fee (measured as a percentage of a fund's upside above a specific threshold), Total Redemption Period, which is the sum of Advance Notice Period and Redemption Period (measured in days), Subscription Period (measured in days) and Style Effect $_t$ (measured as the average flow for a particular category at time t). *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level.

Panel A: Effect of Illiquidity θ_0 Restriction on Fund Flow – Performance Relationship

	Illiquidity θ_0 Restriction	
Variable	Estimate	*t*-value
Intercept	2.093	3.90***
Low Performance$_{t-1}$	0.720	2.20***
Middle Performance $_{t-1}$	0.786	3.01***
High Performance $_{t-1}$	0.870	4.47***
Low Performance$_{t-1}$*Low θ_0	0.538	3.14***
Middle Performance$_{t-1}$*Low θ_0	0.168	0.55
High Performance$_{t-1}$*Low θ_0	-0.692	-3.35***
Standard Deviation $_{t-1}$	-0.021	-2.04*
Log (Size) $_{t-1}$	-0.149	-5.45***
Live	0.208	5.36***
Style effect	0.590	5.41***
Total Redemption Period	0.000	0.83
High Water Mark	0.104	2.30**
Leverage	0.043	1.28
Incentive Fee	-0.001	-0.89
Subscription Period	-0.002	-3.14***
Average Number of Observations	482	
Adjusted *R*-squared	12.7%	

Panel B: Effect of Total Redemption Period and Capacity Constrained Restrictions on Fund Flow – Performance Relationship

	Total Redemption and Capacity Restrictions	
Variable	Estimate	*t*-value
Intercept	2.076	3.82***
Low Performance$_{t-1}$	0.555	1.60
Middle Performance $_{t-1}$	1.076	3.65***
High Performance $_{t-1}$	0.752	1.98*
Low Performance$_{t-1}$*Long Total Redemption	0.598	2.13*
Low Performance$_{t-1}$*Capacity Constrained	0.498	2.82**
Middle Performance$_{t-1}$*Long Total Redemption	-0.521	-1.66
Middle Performance$_{t-1}$*Capacity Constrained	-0.171	-0.56
High Performance$_{t-1}$*Long Total Redemption	0.179	0.39
High Performance$_{t-1}$*Capacity Constrained	-0.735	-2.24**
Standard Deviation $_{t-1}$	0.013	0.37
Log (Size) $_{t-1}$	-0.120	-6.03***
Live	0.139	2.31***
Style effect	0.577	5.29***
Total Redemption Period	0.000	-0.12
High Water Mark	0.096	1.94*
Leverage	0.045	1.33
Incentive Fee	0.000	0.13
Subscription Period	-0.002	-2.92***
Average Number of Observations	482	
Adjusted *R*-squared	12.51%	

Panel C: Combined Effect of All Share and Illiquidity Restrictions on Fund Flow – Performance Relationship

	All Restrictions Combined	
Variable	Estimate	*t*-value
Intercept	2.178	3.74***
Low Performance$_{t-1}$	0.713	1.75
Middle Performance $_{t-1}$	0.891	2.45**
High Performance $_{t-1}$	1.097	2.77**
Low Performance$_{t-1}$*Sum Restrictions	1.064	#
Middle Performance$_{t-1}$*Sum Restrictions	-0.640	#
High Performance$_{t-1}$*Sum Restrictions	-0.514	#
Standard Deviation $_{t-1}$	-0.019	-1.64
Log (Size) $_{t-1}$	-0.156	-5.62***
Live	0.228	5.46***
Style effect	0.576	5.07***
Total Redemption Period	0.000	0.19
High Water Mark	0.094	2.34**
Leverage	0.041	1.10
Incentive Fee	-0.001	-0.33
Subscription Period	-0.001	-0.77
Average Noumber of Observations	482	
Adjusted *R*-squared	14.1%	

#*t*-values are only reported for the individual regressors.

Table VI Fund Flow-Performance Relation with Capacity Constraints: The Cases for Long/Short Equity Hedge and Fund of Funds Categories

This table reports Fama-MacBeth OLS estimates with net flow as a dependent variable for Long/Short Equity Hedge funds (Panel A) and Fund of Funds (Panel B) in the Combined, Live and Defunct databases. This table presents annual results using the Tremont TASS database covering the period of January 1994 to December 2004. Net flows into each fund are defined as the percentage change of net assets of the fund between the beginning of a year and the end of a year net of yearly returns. The dependent variables are three terciles of performance (Low Performance $_{t-1}$, Middle Performance $_{t-1}$ and High Performance $_{t-1}$) at time t-1, standard deviation of returns at time t-1, natural logarithm of hedge fund dollar assets at time t-1, Live Dummy (1 if a fund is in the live database and 0 if a fund is defunct), Advance Notice Period (measured in days), Open to Public dummy (1 if a fund is open to public and 0 otherwise), High Water Mark dummy (1 if a high water market provision is present and 0 otherwise), Leverage dummy (1 if a fund uses leverage and 0 otherwise), Management Fee (measured as a percentage of assets under management), Incentive Fee (measured as a percentage of a fund's upside above a specific threshold), Lockup Period (measured in days), Redemption Period (measured in days), Subscription Period (measured in days) and Style Effect (measured as the percentage of all flows going to a specific style the fund is in compared to other style flows). *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level.

Panel A: Long/Short Equity Hedge Category

	All Funds		Live Funds		Defunct Funds	
Variable	Estimate	*t*-value	Estimate	*t*-value	Estimate	*t*-value
Intercept	3.580	5.47***	4.346	4.64***	3.493	3.03**
Low Performance $_{t-1}$	0.196	0.38	-0.743	-0.48	0.228	0.58
Middle Performance $_{t-1}$	1.251	4.51***	1.431	3.36***	0.956	2.01*
High Performance $_{t-1}$	1.496	3.12**	1.451	1.99*	1.849	3.38***
Standard Deviation $_{t-1}$	-0.039	-4.10***	-0.051	-4.97***	-0.042	-1.87*
Log (Size) $_{t-1}$	-0.204	-6.24***	-0.211	-4.88***	-0.180	-4.93***
Live	0.238	3.87***				
Advance Notice Period	0.001	0.60	0.001	0.49	-0.002	-0.41
Open to Public	0.112	1.00	0.206	1.62	-0.076	-0.51
High Water Mark	0.126	1.64	0.093	0.89	0.230	1.74
Leverage	0.096	2.65**	0.116	2.24**	0.112	1.42
Management Fee	-0.095	-1.99*	-0.122	-1.73	-0.010	-0.06
Incentive Fee	-0.001	-0.11	-0.001	-0.18	-0.024	-0.64
Lockup Period	-0.003	-0.43	0.001	0.14	0.012	0.57
Redemption Period	0.000	-1.85*	0.000	-1.04	-0.002	-1.53
Subscription Period	-0.001	-2.16*	-0.002	-3.11**	0.001	0.86
Average Number of Observations	274		201		73	
Adjusted *R*-squared	15.30%		15.12%		22.09%	

Panel B: Fund of Funds Category

	All Funds		Live Funds		Defunct Funds	
Variable	Estimate	*t*-value	Estimate	*t*-value	Estimate	*t*-value
Intercept	2.544	3.91***	3.190	4.70***	0.612	0.51
Low Performance$_{t-1}$	0.170	0.86	0.192	0.75	0.924	1.27
Middle Performance $_{t-1}$	0.682	1.77	0.538	1.88*	1.141	1.24
High Performance $_{t-1}$	1.194	1.88*	1.270	2.62**	0.811	0.55
Standard Deviation $_{t-1}$	-0.086	-1.86*	-0.100	-1.93*	-0.002	-0.03
Log (Size) $_{t-1}$	-0.145	-4.21***	-0.166	-4.87***	-0.078	-1.31
Live	0.149	2.27**				
Advance Notice Period	0.003	2.02 *	0.003	2.64**	-0.003	-1.05
Open to Public	-0.043	-0.57	-0.126	-1.75	0.226	1.14
High Water Mark	-0.015	-0.22	0.016	0.19	-0.257	-1.02
Leverage	-0.085	-1.35	-0.146	-3.81***	-0.083	0.57
Management Fee	-0.027	-0.74	-0.009	-0.21	0.088	0.66
Incentive Fee	0.000	-0.02	-0.001	-0.36	0.004	0.39
Lockup Period	-0.017	-1.62	-0.012	-2.06*	0.038	1.57
Redemption Period	0.000	-0.62	-0.001	-2.85**	0.004	1.72
Subscription Period	-0.001	-1.55	-0.001	-2.53**	-0.002	-0.59
Average Number of Observations	183		146		40	
Adjusted *R*-squared	8.5%		13.9%		16.87%	

Table VII Fund Flow-Performance Relation: Live vs. Defunct Funds

This table reports Fama-MacBeth OLS estimates with net flow as a dependent variable for all funds in the All, Live and Defunct databases. This table presents annual results using the Tremont TASS database covering the period of January 1994 to December 2004. Net flows into each fund are defined as the percentage change of net assets of the fund between the beginning of a year and the end of a year net of yearly returns. The dependent variables are three terciles of performance (Low Performance $_{t-1}$, Middle Performance $_{t-1}$ and High Performance $_{t-1}$) at time t-1, standard deviation of returns at time t-1, natural logarithm of hedge fund dollar assets at time t-1, Live Dummy (1 if a fund is in the live database and 0 if a fund is defunct), Advance Notice Period (measured in days), Open to Public dummy (1 if a fund is open to public and 0 otherwise), High Water Mark dummy (1 if a high water market provision is present and 0 otherwise), Leverage dummy (1 if a fund uses leverage and 0 otherwise), Management Fee (measured as a percentage of assets under management), Incentive Fee (measured as a percentage of a fund's upside above a specific threshold), Lockup Period (measured in days), Redemption Period (measured in days), Subscription Period (measured in days) and Style Effect $_t$ (measured as the average flow for a particular category at time t). *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level.

	All Funds		Live Funds		Defunct Funds	
Variable	Estimate	*t*-value	Estimate	*t*-value	Estimate	*t*-value
Intercept	2.280	5.44***	2.897	6.22***	1.891	3.58***
Low Performance $_{t-1}$	0.921	5.33***	0.966	4.83***	0.751	2.17*
Middle Performance $_{t-1}$	0.906	6.36***	0.928	3.99***	0.694	3.59***
High Performance $_{t-1}$	0.906	4.00***	0.707	2.91**	1.203	2.27**
Standard Deviation $_{t-1}$	-0.020	-3.08**	-0.020	-1.72	-0.009	-0.78
Log (Size) $_{t-1}$	-0.170	-8.00***	-0.189	-7.86***	-0.124	-5.35***
Live	0.243	4.69***				
Advance Notice Period	0.001	2.03*	0.001	1.12	0.002	1.93*
Open to Public	0.090	1.18	0.194	1.64	0.010	0.13
High Water Mark	0.126	3.67***	0.104	1.98*	0.174	2.90**
Leverage	0.083	3.15***	0.066	1.71	0.141	2.67**
Management Fee	-0.021	-0.77	-0.003	-0.12	-0.074	-1.59
Incentive Fee	-0.002	-0.71	-0.002	-0.79	-0.019	-1.34
Lockup Period	0.001	0.22	0.002	0.26	-0.002	-0.37
Redemption Period	0.000	-0.44	0.000	-0.31	0.000	0.13
Subscription Period	-0.001	-3.02**	-0.001	-3.63***	0.000	-0.11
Style Effect $_t$	0.522	8.34***	0.433	4.19***	0.478	3.80***
Average Number of Observations	692		493		199	
Adjusted *R*-squared	13.38%		13.56%		13.76%	

Table VIII Closed to Investment by Performance Groups

This table reports percentage of funds closed to investment and the average rank and monthly return of the two groups. Only funds from the Live Database are included in the analysis. Each year the percentage of funds closed to investment in the high performance group and the combined middle and low performance group are computed. The average return and average performance rank in each particular style are also reported for each group. The differences between the two groups are reported for all three variables. We also use two TASS Database versions to compute these values. The top information is computed using the OpenToInv variable from the January 2001 TASS Database while the bottom results are computed using the September 2005 TASS Database.

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Panel A: 01/2001 Data											
High Closed %	20.59	35.90	22.06	26.47	18.27	20.33	18.87	17.62	16.75	15.38	18.28
Low/Mid Closed %	11.67	10.98	25.77	19.48	18.53	14.64	15.45	18.83	19.08	19.78	18.89
Difference	8.92	24.92	-3.71	6.99	-0.26	5.69	3.42	-1.21	-2.33	-4.40	-0.61
Closed Avg. Rank	0.552	0.679	0.518	0.538	0.511	0.581	0.585	0.481	0.432	0.422	0.491
Open Avg. Rank	0.504	0.439	0.563	0.466	0.481	0.537	0.514	0.467	0.452	0.450	0.504
Difference	0.048	0.240	-0.045	0.072	0.030	0.044	0.071	0.014	-0.020	-0.028	-0.013
Closed Avg. Return	1.922	0.534	1.389	1.812	1.650	0.929	3.126	0.642	0.175	-0.098	1.516
Open Avg. Return	1.906	-0.154	1.718	1.480	1.453	0.459	2.523	0.578	0.401	-0.031	1.577
Difference	0.016	0.688	-0.329	0.332	0.197	0.470	0.603	0.064	-0.226	-0.067	-0.061
Panel B: 09/2005 Data											
High Closed %	11.11	25.00	16.67	17.72	16.95	20.55	17.77	23.51	22.95	25.12	15.65
Low/Mid Closed %	12.00	14.06	19.79	16.55	16.00	15.69	17.40	16.63	16.67	14.31	16.49
Difference	-0.89	10.94	-3.12	1.17	0.95	4.86	0.37	6.88	6.28	10.81	-0.84
Closed Avg. Rank	0.634	0.651	0.496	0.543	0.568	0.547	0.553	0.590	0.597	0.607	0.522
Open Avg. Rank	0.543	0.540	0.559	0.534	0.530	0.511	0.525	0.539	0.531	0.507	0.519
Difference	0.091	0.111	-0.063	0.009	0.038	0.036	0.028	0.051	0.066	0.100	0.003
Closed Avg. Return	2.771	0.986	1.140	1.879	2.026	0.424	2.962	1.095	0.926	0.634	1.560
Open Avg. Return	2.287	0.436	1.706	1.760	1.587	0.288	2.134	1.040	0.837	0.328	1.597
Difference	0.484	0.550	-0.566	0.119	0.439	0.136	0.828	0.055	0.089	0.306	-0.037

Table IX Drop Reasons by Performance Groups

Data is from Tremont TASS covering the period of January 1993 to December 2003. Drop code reasons are reported by TASS. Each year the frequency for each dead code and performance group were computed. Using this data, the percentage of funds in each dead code for each performance group was also computed. Reported are the average number of funds per year and average yearly percentage in each dead group for all three performance groups.

	Low Performance		Middle Performance		High Performance	
Reason	Number	Percent	Number	Percent	Number	Percent
Fund Closed to New Investment	1	0.60%	0	0.22%	1	0.55%
Fund Dormant	0	0.15%	0	0.09%	0	0.07%
Fund Has Merged	5	4.62%	5	4.67%	4	3.81%
Fund Liquidated	73	52.09%	51	52.50%	42	46.25%
Fund No Longer Reporting to TASS	41	28.50%	30	30.13%	33	35.67%
Not Reported	0	0.00%	0	0.00%	0	0.00%
TASS Has Been Unable To Contact	12	8.70%	7	7.16%	9	8.82%
Unknown	6	5.33%	5	5.25%	5	4.83%

Table X Performance of Hedge Fund Flows

The performance of hedge fund flows is reported for the period of 1994 through 2004. Specifically, the quarterly *GT* measure, time-series average quarterly raw return of flow-weighted and equally-weighted zero-cost portfolios are calculated. The *GT* measure is based on Grinblatt and Titman (1993) and takes the following functional form: $GT_{t+1} = \sum_{i=1}^{N} (w_{i,t} - w_{i,t-1}) \cdot R_{i,t+1}$ where $w_{i,t}$ and $w_{i,t-1}$ are the weight of fund *i* measured by its assets at the beginning of quarters *t* and *t-1*, respectively and $R_{i,t+1}$ is the raw return of the portfolio for quarter *t+1*. The zero-cost portfolios are generated at the beginning of each quarter from 1994 through 2004. Specifically, at the beginning of each quarter, we put each hedge fund into a positive-flows (negative-flows) fund portfolio if the prior-quarter flows are positive (negative). Then a flows-weighted (equally-weighted) zero-cost fund portfolio is formed by going long on the positive-flows fund portfolio weighted by flows (equally) and going short on the negative-flows fund portfolio weighted by flows (equally). All independent variables are presented in percentage terms. The time-series *t*-statistics are also reported. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

	GT (%)	Time-Series *t*-Stat.	Flow-Weighted Zero-Cost Portfolio (%)	Time-Series *t*-Stat.	Equally-Weighted Zero-Cost Portfolio (%)	Time-Series *t*-Stat.
All Categories	0.35	2.17**	0.79	0.48	1.17	1.60
Convertible Arbitrage	0.11	0.68	1.28	0.82	1.64	1.11
Dedicated Short Bias	0.01	0.02	-2.04	-0.28	-1.37	-0.22
Emerging Markets	0.20	0.44	-2.69	-0.81	0.64	0.23
Equity Market Neutral	0.01	0.08	-0.45	-0.23	0.56	0.37
Event Driven	0.15	1.50	-0.60	-0.38	1.70	1.71*
Fixed Income Arbitrage	0.25	2.39**	1.78	1.11	3.92	2.94***
Global Macro	0.06	0.24	-4.00	-0.82	-0.95	-0.69
Long/Short Equity Hedge	0.43	1.90*	4.88	2.36**	2.34	2.26**
Managed Futures	-0.09	-0.45	-0.41	-0.18	-0.40	-0.31
Multi-Strategy	0.59	2.76***	3.26	0.62	6.81	2.27**
Fund of Funds	0.06	0.97	0.26	0.26	0.47	0.51

Table XI Multi-Index Model of Performance of Zero-Cost Equally-Weighted Portfolios of Hedge Funds Formed by Flows

This table reports the results of the time-series regressions of the monthly equally-weighted returns of zero-cost portfolios of long hedge funds with positive flows and short hedge funds with negative flows on asset class indexes and macro factors for the period of 1994 through 2004. Included in the regressions as independent variables are the Russell 3000 index return, difference between the Russell 1000 index return and the Russell 2000 index return (LMS), difference between the Russell 1000 value index return and the Russell 1000 growth index return (VMG), the momentum factor downloaded from Ken French's web site (UMD), the Lehman Aggregate Bond index return, yield spread between BAA bonds and AAA bonds (Credit spread), yield spread between the 10-year Treasury note rate and the 6-month LIBOR (Yield spread), return on the S&P500 at-the-money call option (ATM Call), the MSCI emerging market stock index return, the MSCI emerging market bond index return, the 6-month LIBOR, the Federal Reserve dollar index return, the gold index return, oil price change, and change in the volatility index (VIX). At the beginning of each quarter from 1994 through 2004, we put each hedge fund into the positive-flows (negative-flows) fund portfolio if the prior-quarter flows are positive (negative). High θ_0 Funds are funds with θ_0 greater than or equal to 0.86. Low θ_0 Funds are funds with θ_0 lower than 0.86. All estimates are presented in percent per month. All *t*-statistics are adjusted for heteroscedastocity and autocorrelation using the Newey-West (1987) method with 4 truncation lags. The *p*-values of the Chow (1960) test for the equality of the set of regression coefficients for funds with high and low θ_0 are also reported. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

	All Funds		High θ_0 Funds		Low θ_0 Funds	
Variable	Estimate	*t*-Stat.	Estimate	*t*-Stat.	Estimate	*t*-Stat.
Intercept	1.62	2.35***	2.08	2.46**	1.12	1.37
Russell 3000	0.060	1.65*	0.098	2.61***	0.016	0.33
LMS	-0.019	-1.42	0.015	0.62	-0.042	-1.94*
VMG	0.012	0.78	0.025	0.83	-0.013	-0.68
UMD	0.037	3.81***	0.032	2.56**	0.030	2.26**
Lehmann Aggregate Bond	0.062	0.68	-0.004	-0.04	0.057	0.77
Credit Spread	-0.67	-2.09**	-1.02	-2.41**	-0.25	-0.62
Term Spread	-0.14	-1.89*	-0.14	-1.84*	-0.18	-1.31
ATM Call	-0.002	-1.48	-0.003	-1.66*	-0.002	-1.23
MSCI Emerging Stock	-0.042	-4.25***	-0.052	-3.38***	-0.045	-3.82***
MSCI Emerging Debt	-0.075	-0.75	-0.044	-0.41	0.054	0.47
LIBOR	-2.39	-2.23**	-2.83	-2.31**	-2.00	-1.57
USD	-0.055	-0.73	-0.027	-0.29	0.022	0.24
GOLD	-0.022	-1.51	-0.003	-0.17	-0.039	-2.15**
OIL	0.009	1.55	0.013	1.38	0.009	1.52
Change in VIX	0.010	0.46	-0.014	-0.62	0.036	1.59
Number of Observations		132		132		132
Adjusted *R*-squared		0.24		0.27		0.14
p-value for Chow-test				0.02		

Figure 1 Fund Flow-Performance Relation: All, Live, and Defunct Funds

This figure depicts fund flow-past performance relationship for All, Live and Defunct databases. Net flows into each fund are defined as the percentage change of net assets of the fund between the beginning of a year and the end of a year net of yearly returns. The dependent variables are three terciles of performance (Low Performance $_{t-1}$, Middle Performance $_{t-1}$ and High Performance $_{t-1}$) at time t-1.