Who are the Smartest Investors in the Room? Evidence from U.S. Hedge Funds Solicitation

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ABSTRACT

This paper examines the efficiency of investment decisions by hedge fund clients. While highly sophisticated, their investment decisions are made difficult by the decentralized nature of the industry. We use SEC Form D filings to examine, for the first time, inflows and outflows across the entire industry. We document that only examining net flows masks high turnover and convex responses of inflows and outflows to performance. Furthermore, we find evidence of a "smart money" effect, which surprisingly is driven by inflows rather than outflows. Finally, we also find that investor flows are smarter when investors must anticipate funds' liquidity restrictions.

JEL Classifications: G11 (portfolio choice), G23 (private financial institutions), G32 (financial risk management)

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I. Introduction

Hedge fund clients are some of the most sophisticated investors in the money management industry. In the United States, hedge fund investors are restricted to either large institutional investors, such as pension funds, endowment funds, and sovereign wealth funds, or "sophisticated" persons who are deemed to have sufficient investing experience and knowledge via their substantial net worth. Given their backgrounds, these investors should make efficient decisions when allocating capital.

In practice, however, this may not be the case for several reasons. First, the hedge fund solicitation market is private and decentralized, which leads to significant search costs. Indeed, hedge funds are prohibited from general solicitation, including advertising.[1] Some information is available through commercial hedge fund databases, [2] but these do not give a full picture of the market because reporting is voluntary.[3] This makes it very difficult for investors to evaluate hedge funds' comparative performance. Second, hedge fund managers are notoriously secretive about their strategies, making in-depth evaluation of managers difficult. Third, some hedge funds have significant liquidity restrictions that could prevent investors from reacting to salient information.

To date, little research has examined the effects of these factors on the quality of hedge fund investors' investment decisions. A likely reason for the lack of prior work is that a thorough assessment of investment decisions requires detailed information about both hedge funds' inflows and outflows, which are not included in any commercial hedge fund database. Hedge fund

[1] In theory, the restriction on advertising was lifted by the 2012 JOBS act. In practice, few hedge funds have taken advantage of this easing due to remaining regulatory uncertainty.
[2] Hedge fund databases are the only public source of information about the performance of hedge funds. Annual subscriptions entail modest costs, on the order of $5,000 for a single database.
[3] Hedge Fund Research (2014) estimates that the hedge fund industry manages approximately $2,628 billion as of the end of 2013. On the other hand, the Alternative Fund Administrator Survey 2014 reports a total of $3,791 billion in hedge fund AUM as of 2013. This has no detail about individual hedge funds, however, and only accounts for hedge funds that have an outside administrator. Therefore, the total size of the hedge fund industry must vastly exceed the usual estimate of $2.6 trillion.

databases only allow for an approximation of *net* flows, which can hide important information about investor behavior. The same restriction affects studies of mutual funds.[4]

In this paper, we exploit a new data source to overcome prior data deficiencies and examine these aspects of the hedge fund solicitation market. All hedge funds that attract at least one U.S. investor are required to file Form D with the Securities and Exchange Commission (SEC). This form includes the historical total amount of the offering sold and the number of investors, and must be updated every twelve months over the course of the offering. Using time series changes in historical total sales (number of investors), we can compute inflows (number of new investors). Coupled with inferred net flows from commercial databases, we can also estimate outflows for a subgroup of hedge funds that report to both sources.

Additionally, because the Form D sample represents the complete U.S. hedge fund solicitation market, we can for the first time provide a quantitative estimate of database coverage for the entire hedge fund industry. Since listing in a hedge fund database is akin to advertising (e.g., Jorion and Schwarz (2014)) and advertising is expected to reduce search costs (e.g., Sirri and Tufano (1998)), quantifying the fraction of the industry available in public databases gives insights into hedge fund investors' search costs.

Using these data, we document several novel findings concerning the hedge fund solicitation marketplace. First, our results suggest that search costs for investors are likely high. We demonstrate that commercial hedge fund databases account for a very small portion of the hedge fund market.[5] Over the 2009 to 2014 period, approximately 22,800 hedge funds file Form D with

[4] Most researchers use the CRSP database, which only reports NAVs, and use the Sirri and Tufano (1998) approach to calculate net flows. More recently, however, several papers have accessed directly SEC filings, which give additional information on inflows and outflows (e.g., Bergstresser and Poterba (2002), Johnson (2010), Cashman et al. (2012)).

[5] Although we only formally use two databases in this paper, we have preliminarily matched Morningstar/CISDM to the Form D data as well. This additional database increases the coverage by only a small amount. Given the information in Agarwal et al. (2009) concerning hedge fund database coverage, it is unlikely that additional databases would significantly affect our conclusions.

the SEC, with total lifetime sales exceeding $6 trillion. Only 3,800 (17%) of these funds are included in either the Hedge Fund Research (HFR) or the Lipper Trading Advisor Selection System (TASS) databases. In dollar terms, out of $3.2 trillion of new sales over the 2009-2014 period and 400,000 new investors reported in Form Ds, only $473 billion of new sales (15%) and 100,000 (25%) of new investors are for funds listed in these two commercial databases. This confirms Edelman et al.'s (2013) argument that most large hedge funds do not report to any commercial database. However, we find that coverage is even lower for smaller funds. This is precisely the segment for which the information acquisition process is most difficult. Thus, there is a large, informal backchannel of solicitation that accounts for a majority of hedge fund purchasing decisions. We therefore conclude hedge fund investors likely experience high search costs when making investment decisions.[6]

Next, we use our data to expand our knowledge concerning the determinants of hedge fund investor flows. For mutual funds, the contemporaneous and prior flow-performance relations are reported as a convex function (e.g., Sirri and Tufano (1998) and Chevalier and Ellison (1997)), implying that flows increase at an accelerated rate for highly performing funds. Instead, we find a linear relation between net flows and both concurrent and prior year performance for hedge funds. Examining only net flows, however, masks how hedge fund investors make investment allocations because hedge funds have a very high level of investor turnover. We find that the average hedge fund has annual inflows equal to 30% of prior year assets, has annual outflows equal to 26% of prior year assets, and expands its number of investors by 38% annually. These numbers are much higher than for mutual funds, as reported in Cashman et al (2012).

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[6] Indeed, Barclays (2013) estimates that intermediaries such as funds of hedge funds (FoHFs) and investment consultants account for two-thirds of flows to hedge funds. FoHFs charge annual fixed fees of 0.80% on average, plus incentive fees, for access to their portfolio of hedge funds. Among consultants, Albourne is the largest, and offers access to a database of more than 20,000 funds with detailed due diligence on 700 funds (http://www.albourne.com). For its broader services, it charges an annual flat fee of $400,000, which is low by industry standard.

Our decomposition of inflows and outflows yields important additional insights. The reported linear net flow-performance relation is driven by two non-linear effects. Inflows and changes in the number of investors have the same convex flow-performance relation documented for net flows in the mutual fund industry. At the same time, however, we observe that outflows display a reverse convex flow-performance relation. In other words, funds in the lowest performance quintile have much higher outflows than extrapolated from the other four performance quintiles. This result is inconsistent with the mutual fund industry where the net flow-performance relation is dominated by inflows since outflows are found to be invariant to past performance (e.g., Bergstresser and Poterba (2002), Johnson (2010), Cashman et al. (2012)). This lack of sensitivity has been attributed to several causes, including lack of monitoring, a disposition effect, and the confounding effect of random liquidity needs or tax considerations. Instead, our results suggest that hedge fund investors behave very differently.

Next, as in the case of mutual funds (e.g., Gruber (1996), Zheng (1999), Keswani and Stolin (2008)), we document strong evidence of smart money effects in hedge funds.[7] Even after controlling for performance persistence, higher net flows predict higher future returns as well as a lower probability of fund death. Interestingly, we find that investor flows are smarter when funds' have investor liquidity restrictions. These results indicate investors anticipate liquidity restrictions when making investment decisions. Finally, as with mutual funds, we find that the smart money effect is driven by inflows rather than outflows. Finding that outflows do not seem informative is surprising for a number of reasons, given the differences between the hedge fund and mutual fund industries.[8]

[7] To date, only two working papers examine the smart money effect in hedge funds. Baquero and Verbeek (2009) find mixed evidence that net flows into hedge fund are smart. Ozik and Sadka (2010) find evidence of smart money but suggest this is simply due to investors anticipating price pressure from flows rather than identifying superior managers.
[8] Although outflows do not seem to predict performance, removing money from the worst performing hedge funds is still rational due to performance persistence in the industry.

First, the opaque nature of the hedge fund industry, relative to the mutual fund industry, should create an informational advantage for existing investors. For example, existing investors typically have more detailed and frequent access to portfolio information and the fund manager. Given that insider profits should be higher when asymmetric information is higher (e.g., Kyle (1985) and Gloston and Milgrom (1985)), we would expect outflows to be relatively more informed for hedge funds as compared to mutual funds. Second, outflows could be non-informative due to liquidity restrictions on outflows, such as lockups, long redemption periods, and gates, which prevent current investors from exploiting their informational advantage efficiently. However, we find outflows for funds with fewer restrictions do not seem to be informative either.

Third, outflows may not be predictive due to unplanned liquidity needs. While individual investors may be subject to liquidity shocks, institutional investors, such as pension funds, have fairly well defined liquidity needs. Yet we still find institutional investors' outflows do not seem predictive of performance or fund death as well. Finally, outflows could not be smart due to the compensation structure of hedge funds. Investors in funds that are below the high water mark (HWM) have a disincentive to switch to another fund. If investors remain in the current fund, future positive returns will not be subject to the incentive fee until the HWM is met, whereas investments in new funds will be subject to the incentive fee. As a result, investors may remain with funds below the high watermark, even if they believe they could underperform on a gross return basis, due to the incentive fee effect. However, we rule this out as a cause of our results.

Overall, our results add significantly to several strands of literature. First, this paper adds to our knowledge of the private solicitation market for hedge funds. To our knowledge, this is the only paper that uses Form D information for inference about the size of the industry.[9] We show that the solicitation market for hedge funds is significantly larger than that implied from commercial

[9] Clifford et al. (2013) also collect SEC Form D to examine the effect of outside boards on offshore hedge funds.

databases, indicating it is highly decentralized in nature. While Edelman et al. (2013) show that some of the largest hedge fund companies do not report to databases, we document that this issue is actually more pervasive for smaller hedge funds.

Second, we add to the literature regarding the determinants of hedge fund flows. This is the first paper to examine inflows, outflows, and investor changes in the hedge fund industry. While our net flow findings are similar to prior research (Getmansky et al. (2014), Baquero and Verbeek (2009)), we document that simply examining net flows hides significant information as well as non-linear relations between inflows and outflows and performance. Inflows and new investors react much more strongly to the highest performance funds, which is similar to the mutual fund industry. However, unlike mutual funds, outflows react strongly to poor performance. This demonstrates that hedge fund investors are stronger monitors than mutual fund investors.

Third, we provide new findings on smart money. We document that sophisticated hedge fund investors' net flows can predict future performance as well as fund death. We also document that this effect is due to inflows rather than outflows, even though current hedge fund investors likely have an informational advantage relative to new investors. We document that the "dumbness" of outflows are not due to liquidity restrictions, liquidity needs, or potential fee advantages.

Finally, we find that investors anticipate liquidity restrictions when making investment allocation decisions. While Getmansky et al. (2014) imply that investors endogenize liquidity restrictions due to shape changes in the net flow-performance relation, we provide direct evidence that outflow restrictions have an effect on investment decisions.

This rest of the paper is structured as follows. Section II describes the data sources and Form D. Section III compares the hedge funds common to Form D and commercial databases. Section IV discusses the relation between net flows, inflows, outflows and investor changes and current and prior year performance. Section V then examines the smart money effect, which relates flows to future performance and fund death. Finally, Section VI concludes.

II. Data

We rely on two main data sources for this paper. The first consists of Form D filings made to the Securities and Exchange Commission (SEC) and the second is the union of two commercial hedge fund databases. We discuss each dataset below.

A. SEC Form D

The Securities Act of 1933 (1933 Act) requires any offer to sell securities to U.S.-domiciled investors to register with the SEC. Companies, however, may use an exemption under Regulation D to offer and sell securities without having to register with the SEC. Regulation D establishes three exemptions from Securities Act registration (Rules 504, 505, and 506).[10] Hedge funds typically rely on Rule 506, which allows unlimited fund-raising but broadly requires the securities be offered to accredited investors only.

Companies that want to take advantage of these private placement exemptions still need to file a Form D with the SEC. The SEC (2008) states, "Form D serves as the official notice of an offering of securities made without registration under the Securities Act in reliance on an exemption provided by Regulation D." This form must be filed within 15 days of the first sale of securities, and annually thereafter if the offering is still "continuing."[11] Form D serves as a means to collect data for the SEC as well as for the public, and to enforce federal securities laws. Failing to file this form

[10] Rule 504 provides an exemption for offerings not exceeding $1,000,000. Rule 505 provides an exemption for offerings not exceeding $5,000,000, with no more than 35 "purchasers". Rule 506 provides an exemption for an unlimited amount, with no more than 35 purchasers. Purchasers specifically exclude "accredited investors."
[11] An offering is continuing, or active, if the fund is accepting additional money from either new or existing investors.

may constitute a violation of securities laws and disqualifies an issuer from using this exemption in the future. In addition, it could lead to a right of rescission for the investors, e.g., if they lose money.

In practice, this means that all hedge funds selling to U.S. investors should file Form D, which thus provides a full registry of this universe. Exceptions are funds that startup operations but are never able to attract any outside U.S. investor. However, these funds are likely to stay small and not last very long. We discuss this issue later.

Starting in March of 2009, the SEC required electronic filing for Form D.[12] Form Ds include several descriptive items, including the name of the issuer, the fund entity type, the types of exemptions claimed, the date of first sale, the minimum investment amount, the total number of investors, and the cumulative amount sold (to all investors, not just U.S. investors). The investor and sales number represent the total history instead of current numbers, such as assets under management (AUM) or current number of investors.[13] Prior to 2009, Form Ds only needed to be amended if certain terms changed. However, starting in 2009, annual amendments became required even if the terms of the filing did not change. This creates an annual time series of changes in the data.

We collected the electronic forms from the SEC's website over the January 2009 to June 2014 period.[14] To identify hedge funds, we focus on Form Ds indicating that the offering is within the "pooled investment fund" industry group, with subcategory defined as either "hedge fund" (75% of our total) or "other investment fund" (25% of total). Summary statistics for our Form D sample are reported in Table I.

[12] The history of Form D is available at: https://www.sec.gov/answers/formd.htm

[13] In some cases, it is clear that funds are reporting current data rather than total historical data. When calculating new sales and new investments, we eliminate these data points.

[14] Scanned forms from January to March 2009 were added to our registry to complete the 2009 calendar year.

<Insert Table I about here>

Over our sample period, a total of 65,362 filings occurred. These filings are made by 22,803 different funds, or about 2.9 filings per fund on average. As of the last filing of each fund, the total amount of aggregate sales sums to $6 trillion. Out of this, $3.3 trillion were raised over the 2010 to 2014 period alone. Given that these totals represent only hedge funds with U.S. investors, the actual amount of money raised by the entire hedge fund industry is surely much higher than $6 trillion. The current size of the industry, however, is based on assets under management. This does include total sales as noted above, plus the funds' organic growth, but minus total redemptions. Regardless, these data suggest that the size of the industry is much larger than previously thought.

At the typical fund level, the average (median) fund has been offered to investors for approximately 12 (4) years. Total historical sales average $311 million per fund, and about $112 million per year. The total number of investors averages 77 across funds, with about 13.7 new ones per year.

Finally, the industry is about evenly split in dollar terms between funds classifying themselves as "hedge funds" and as "other investment funds". The latter includes funds of funds and global macro funds, which account for 27% of the total number of funds only.[15] Hence, their average size is much larger than pure hedge funds, with about $523 million in total sales, which is roughly twice the $243 million average for the other category. Indeed the average fund of funds must be bigger than the average hedge fund.

[15] In untabulated results, we examine what drives our matches rates for our overall sample as well as the two subgroups. We find the primary difference between the two subgroups is more CTAs and funds of funds label themselves as "other" funds.

B. Commercial Hedge Fund Databases

Reporting funds are derived from the combination of two widely-employed hedge fund databases, TASS and HFR.[16] We use the July 2014 version of the TASS database, which has 19,601 funds, and the July 2014 version of the HFR database, which has 21,723 funds. Both databases contain live and defunct funds since 1994, which eliminates survivorship bias after that date. Funds that are common to both databases are identified using fund names, with characteristic data defaulting to HFR. The final database consists of 32,268 individual funds. These are then matched against the Form D sample using fund names as there is no unique identifier common to both data sources. The funds contained in both samples are described next.

III. Form D and Commercial Database Overlap

Unlike commercial databases, our Form D sample has information on every hedge fund that has been sold to a U.S. investor. For example, Edelman et al. (2013) document that many large hedge funds are not listed in commercial databases. However, Form D filings are required for their missing funds. As an illustration, Edelman et al. (2013) specifically note that well-known fund companies such as Paulson Management LLC and Och-Ziff Capital Management Group are missing from their commercial database sample. In our Form D sample, Och-Ziff lists 44 funds with total sales of $46 billion and almost 4,000 investors. Thus, only a subset of Form D funds can be matched to the commercial databases. Next, we examine the characteristics of listed funds.

A. Overall vs. Matched Form D Characteristics

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[16] These are widely used databases, as in Ackermann et al. (1999), Liang (2000), Agarwal et al. (1999), Jorion and Schwarz (2014).

Table II describes Form D characteristics of our matched sample. These numbers can be compared to the total Form D sample described in Table I. We match a total of 14,581 Form Ds and 3,816 funds to HFR and TASS. This represents only 22.3% of the Form D filings and 16.7% of the Form D funds. Focusing on sales amounts leads to similar conclusions. Our matched sample has about $1 trillion in total sales, which represents only 17% of the entire Form D sample of $6 trillion. Statistics for the total number of investors are similar. However, there are differences across the Form D subgroups. While the average match rate is 16.7% for the entire sample, it is higher (21.5%) for the hedge fund Form D sample and considerably lower (4.1% only) for the other subcategory. Even if we based our coverage estimates on funds that self-identify as "Hedge Fund," our match rates are still quite low.

<Insert Table II about here>

Overall, we find that these commercial databases cover only a small fraction of the industry. The natural question is whether the smaller sample is representative of the total Form D sample. Comparing Tables I and II, the average fund characteristics are largely similar. The entire Form D sample and matched sample have approximately the same average total sales (about $300MM) and total number of investors (about 80). The two groups largely have the same amount of inflows and new investors on a yearly basis as well.

Although the average fund may be similar across our two samples, this does not necessarily mean that they have the same distributional properties. As mentioned previously, Edelman et al. (2013) find that most large hedge fund companies do not report to commercial databases. Agarwal et al. (2013) suggest that the tails of the distribution of the entire hedge fund return universe are missing from commercial datasets.

We thus compare whether the match rates are consistent across the various levels of Total Sales and Total Investors on the Form D filing. We also examine whether changes in Total Sales (Inflows) and number of investors (New Investors) have similar match rates across their entire distributions. Each year we rank all Form D funds independently by these values and then group funds into deciles. In Table III, we report the average characteristic values for each decile as well as the proportion of funds appearing in the commercial databases. To capture the extremes of the distributions, we report the top 2%, 1%, and 0.5% characteristics.

<Insert Table III about here>

The table reveals systematic differences across the distributions. Match rates for Total Sales and Number of Investors are not constant but increase nearly monotonically as the values increase. Small funds, as well as funds with few investors, tend to report less to databases. For example only 9.5% of funds in the lowest sales decile report to a commercial database. In contrast, the ratio is 27.8% of funds in the largest decile. This monotonic function is probably correlated with performance: Advertising is less useful for small funds with poor performance, and vice versa. Hence, large funds do not proportionately hide from databases. Even so, consistent with Edelman et al. (2013), the match rate for the very largest funds, in the top 0.5%, is lower than the rest.

Inflows and investor changes reveal an interesting pattern. The match rate increases slightly from the lower deciles and then tapers off around 30%. Unlike total sales, the match rate for the extreme inflow events is similar to other deciles. This match pattern is also likely related to listing decisions. Funds only list after having good performance, which leads to higher sales in aggregate, but once funds list, their performance falls in line with the overall industry.

B. Onshore vs. Offshore Funds

Since a fund is required to file a Form D only if it has one or more U.S. investors, it seems likely that offshore funds in commercial databases are much less likely to file a Form D.[17] Additionally, onshore and offshore funds with U.S. investors likely serve different clientele. For example, given that onshore funds must pay U.S. federal income taxes, it is more likely that onshore funds are geared to taxable U.S. investors such as individuals or family offices. On the other hand, U.S. investors that are tax-exempt, such as pension funds, should invest in offshore hedge funds because the latter are not subject to U.S. taxes. In addition, non-U.S. investors should invest in offshore funds. This section examines whether onshore and offshore funds do indeed cater to different investor types by examining differences between onshore and offshore funds along several dimensions. Results are presented in Table IV.

<Insert Table IV about here>

Panel A compares match rates across onshore and offshore funds for each year. On average, we find a Form D filing for 44% of onshore funds in commercial databases but onlyfor 6.5% of offshore funds. While one may expect all onshore funds to have U.S. investors, funds can list in a commercial database without filing a Form D first. Many of these funds may never be able to attract a U.S. investor. Indeed, in untabulated results, we find that such funds are significantly smaller than those that do file a Form D.

Comparing fund characteristics in Panel B, we find significant evidence that offshore funds have more institutional clients, as hypothesized. On average, offshore funds have almost twice the amount of total and annual sales but yet have far fewer total investors. Indeed the average fraction

[17] In this case, we are defining offshore hedge funds as any non-U.S. fund.

of ownership, obtained by dividing one by the number of investors, is 17.8% for offshore funds vs. 7.7% for onshore funds.[18]

Finally, because we will examine liquidity restrictions later, we note that the average fund has a notice period of about 50 days, and a long lockup around 90 days. The median lockup is zero, however, which indicates that the distribution of lockup periods varies substantially across funds.

IV. Net Flows, Inflows, Outflows, and New Investors

Prior studies examining hedge fund investor behavior have been limited to *net* flows. In contrast, the Form D information allows us to recover both inflows and outflows, as well as the changes in the number of investors.

A. Creation of Flow Variables

Traditionally, flow information is limited to net flows, derived from consecutive net asset values (NetAsset) and organic growth, as in Sirri and Tufano (1998):

$$\text{NetFlows}_t = \text{NetAssets}_t - \text{NetAssets}_{t-1}(1+R_t) \tag{1}$$

where R_t is the total return. This assumes that all flows occur at the end of the period, or time *t*.[19] Typically, this dollar number will be scaled by initial net asset value, like all other dollar measures.

Net flows hide inflows and outflows, however. From Form D, the cumulative sales information allows us to recover annual inflows

$$\text{Inflows}_t = \text{CumulativeSales}_t - \text{CumulativeSales}_{t-1} \tag{2}$$

Hence, outflows are derived from

[18] Aragon et al. (2014) also compare onshore to offshore funds.
[19] In untabulated results, we assume that flows occur at the beginning of the period rather than the end of the period. Our findings are economically and statistically similar.

$$\text{Outflows}_t = \text{Inflows}_t - \text{NetFlows}_t \tag{3}$$

The number of new investors can also be calculated using consecutive Form D filings.

B. Summary Statistics and Flow-Performance Relation

Table V reports summary statistics for our investor flow measures. To control for outliers, we winsorize flows at the 1st and 99th percentiles and only include funds greater than $1 million.[20] Panel A reports our four average flow measures by year. Panel B ranks funds into quintiles within their style based on performance in the same period as the flow. Finally, Panel C performs a similar analysis, except that funds are ranked within their styles on their returns during the prior year.

<Insert Table V about here>

We find that net flows do hide a significant amount of underlying investor flows. While the average net flow is 16% per year, the average inflow and outflow amounts are 30% and 26% per year, respectively. Investor changes are also substantial, with an average increase of 38% per year. Reflecting the 2008 global financial crisis, inflows were lowest in 2008 while outflows were largest in 2009.

From Panel B, net flows, inflows, and investor changes react immediately to performance, increasing in an almost linear fashion from the lowest performance quintile to the highest performance quintile of the same year. For example, inflows into the worst-performing funds are

[20] In Table V, the difference of the inflow and outflow amounts does not equal net flows. This happens for two reasons. First, most importantly, the numbers are reported after winorizing. Since we winsorize each flow variable individually, the winsorizing affects the average values with different magnitudes. Second, we are implicitly computing outflows. This leads to errors that are easy to spot since outflows should always be non-negative. Thus, to control for errors, we delete any outflow computations that lead to negative values. This happens for less than 10% of our observations. Keeping these negative outflow values or removing the sales and net flows related to negative outflow values does not affect our results in the rest of the paper.

17% lower than for the best-performing funds. Interestingly, outflows do not display a similar pattern and are relatively more constant. This could be due to the delayed effect of lockups or gates, which restrict outflows immediately around poor performance. Such restrictions do not apply to inflows, however.

Panel C shows that all investor flows strongly react to performance the previous year. Net flows and inflows also experience a near-monotonic relation with prior performance. Inflows, however, have a much more pronounced convex relation than net flows, which have a fairly linear relation. Like inflows, new investor changes are also fairly convex. Unlike Panel B, however, outflows are very strong for the worst-performing funds. For example, outflows from the worst-performing funds are 6% higher than for the best-performing funds. This is probably because enough time has elapsed to clear the notice and lockup periods. These results significantly differ from the mutual fund industry where outflows are similar across all performance groups (e.g. Johnson (2010) and Cashman et al. (2012)). The relations in Panels B and C are also graphed in Figure 1.

<Insert Figure 1 about here>

For formal tests of the relation between performance and flows, we run regressions similar to Sirri and Tufano (1998), Getmansky et al. (2014), and Jorion and Schwarz (2014). The dependent variables are the four investor flows discussed previously. To measure performance, we include two piecewise-linear variables. *Low Perf. Rank* is the minimum of the fund's performance rank within its style or 50%, whichever is lower. *High Perf. Rank* is the minimum of the fund's performance rank minus *Low Perf. Rank* and 50%. So, for example a performance rank of 25% would have values of 25% and 0%, respectively; a performance rank of 85% would have values of 50% and

35%. These two variables allow us to capture non-linear effects. In the absence of non-linearities, one would expect positive and similar performance rank coefficient for net flows, for inflows, and negative and similar coefficient for outflows. Other independent variables include fund characteristics as well as style averages for the dependent variables. Panel A (B) ranks funds based on their performance within the concurrent (previous) period. Results are reported in Table VI.

<Insert Table VI about here>

Even after controlling for various fund characteristics, we find similar relations between performance and flows to those found using simple portfolio sorts. Using concurrent performance, the relation is largely linear between net flows and performance. This hides, however, non-linear effects for inflows and outflows. Inflows are more sensitive to the upside, contrary to outflows which are strongest for lower-ranked funds. The results are similar using prior performance, although the magnitude of the coefficients and their statistical significance are generally larger. Also, net flows and inflows are negatively correlated with risk, as measured by the standard deviation over the prior year, as expected. Next, flows decrease with size and increase with the management fee, both indicators of future performance.

The liquidity restriction variables are of significant interest given that they could prevent investors from reacting to time sensitive information. Higher redemption restrictions do not seem related to outflows in the concurrent nor prior period.. We do find, however, that higher liquidity restrictions reduce inflows as well as the number of investors. This indicates that investors may be anticipating the effect of outflow restrictions before they commit capital.[21]

In summary, we find that hedge funds have large amounts of inflows and outflows each year that are understated by simply looking at net flows. Inflows and outflows are related to current and past year returns in a different fashion, which is hidden when focusing only on net flows. The next section examines the “smart money” effect, which involves future returns.

V. Smart Money

Prior work in the mutual fund industry has found that mutual fund investors seem “smart,” meaning that net inflows go into funds that provide better future returns (e.g., Gruber (1996) and Zheng (1999)). Keswani and Stolin (2008) document that this effect is due to inflows from new investments rather than existing investors leaving the fund. They suggest two reasons for this. First, mutual fund investors could suffer from the “disposition” effect, a type of behavior where the investor hangs on to losers and sells winners (e.g., Odean (1998)). Second, fund redemptions could be due to factors unrelated to future performance, such as liquidity needs or taxes.

In contrast, there are reasons to believe that these factors could be significantly mitigated in the hedge fund industry. First, hedge fund investors should be significantly more sophisticated than mutual fund investors. Onshore hedge fund investors must have significant net worth to qualify as accredited investors, suggesting they are more financially literate. Offshore hedge fund investments are mostly made by large institutional investors, such as pension funds. Additionally, the average

[21] In untabulated results, we rerun our regressions interacting liquidity restrictions with performance. We find no significant effects. Additionally, because flows are autocorrelated, we also include prior flows as a variable. Again, our results are largely unchanged.

hedge fund investor holds a large fraction of the fund, certainly much larger than the average mutual fund investor. Large block-holders are expected to better monitor funds.[22]

Second, outflows could be more informative for another reason, which is the informational advantage of existing hedge fund investors compared to new investors. Since hedge funds are less regulated than such publicly offered funds as mutual funds, they have limited reporting requirements. In addition, hedge fund managers are notoriously secretive about their strategies and portfolios. Thus, there is very little public information available about hedge funds.[23] Current investors, however, are likely to have access to better information on the funds. For example, Brown et al. (2012) document that current investors in many funds see some level of portfolio information, which would allow current investors to better evaluate manager skill. Outflows must come from current investors. Admittedly, inflows could represent investments by new investors or additional purchases from existing investors. So, inflows could also reflect this informational advantage.

Third, investments in hedge funds are known to be generally much less liquid than mutual funds. As a result, most hedge fund investments should be made with a longer horizon in mind. Pension and endowment funds, which are typical large hedge fund investors, have well-known future cash needs and are thus less prone to liquidity shocks. Therefore, compared to mutual funds, outflows are less affected by liquidity needs and could reflect information about future returns. On the other hand, lockups and other outflow restrictions could dim their predictive power.

Given the large institutional differences between mutual fund and hedge fund investors and the industries' structures, we would expect to see net flows are informative about future

[22] See for instance Shleifer and Vishny (1986) for the case of corporate control.
[23] See Agarwal and Jorion (2012) for a discussion of the costs and benefits of offering transparency.

performance. We also expect that outflows will be more informed in the hedge fund industry than the mutual fund industry.

A. Return and Death Prediction

We first examine the smartness of hedge fund investors by examining the ability of investor flows to predict performance and fund death. We begin by calculating the funds' cumulative style-adjusted returns for the 1-, 3-, 6-, and 12-month periods after the Form D filing. Results are reported in Table VII. Panel A regresses these returns on the prior period within style performance rank as well as the prior period net flow, inflow, outflow, and investor change. Prior performance is included because previous research finds that hedge fund performance is persistent.[24] As a robustness check, Panel B replaces the performance ranks by dummy values representing rankings into quartiles. The models are run with an intercept term; thus, the lowest quartile group is omitted.

<Insert Table VII about here>

As in previous research, we find that performance is strongly persistent, even after one year. For example, in Panel A, a coefficient of 5.1 for the 12-month return implies that a fund in the top performance rank (100%) generates 5.1% in excess returns in the following year relative to a fund in the bottom rank. In Panel B, the coefficient implies that a top quartile fund will outperform a bottom quartile fund by approximately 3.5% in the following period.

[24] Baquero et al. (2005), for example, report evidence of persistence at a 12-month horizon, even after correcting for look-ahead bias. Jagannathan et al. (2010) find evidence of persistence over three-year horizons. Kosowski, Naik, and Teo (2007) report mild evidence of persistence using Ordinary Least Squares alphas but much stronger evidence in a Bayesian framework. In another study, Aggarwal and Jorion (2010) find that new funds that do not backfill generally have higher performance persistence than other funds.

Even after controlling for performance persistence, we find evidence of a smart money effect for hedge funds. Net flows are strong predictors of future performance, particularly at the 3-month and 6-month horizons, while the 12-month coefficients are also large but not significant due to the loss of power from the greater overlap. For example, a coefficient of 0.3 for the 12-month return implies that an increase of 100% in net flows is associated with 0.3% in excess returns over the following year. This net flow increase corresponds to a doubling of AUM. Interestingly, we find that this smart money effect is driven by new investments. The coefficients on inflows and investor changes are statistically significant, in contrast to those on outflows.

Next, we examine the ability of investors to predict fund death. Indeed, hedge funds have a very high attrition rate (e.g. Jorion and Schwarz (2014)), which is much higher than mutual funds. Thus, the prediction of fund death is important given potential fund liquidation costs and lock up of investor money during the liquidation process. Table VIII reports results of fund death prediction using Cox proportional hazard models which controls for the censoring issue. The dependent variable is set at one if the fund dies, and zero otherwise. As in the flow regressions, we include various fund characteristics, as well as size and prior period performance. The four flow measures are included in separate models.

<Insert Table VIII about here>

As in Table VII, we find that hedge fund investors are smart in the sense that decreasing net flows and numbers of investors significantly predict future fund death.[25] However, this result is again driven by inflows rather than outflows. Otherwise, the probability of fund death increases

[25] Because we also include end of prior period size, there is no mechanical relation between prior period flows and fund death. The impact of flows on fund size is incorporated into the size control.

with lower performance, lower assets, and investment restrictions, which confirms results reported in Chan et al. (2006).

In summary, although existing hedge fund investors likely have an informational advantage over new hedge fund investors, we find that outflows do not lead to better predictions of fund performance or death. Outflows may be noisy performance indicators due to liquidity restrictions, liquidity needs, or the hedge fund industry fee structure. We investigate these possibilities in the following sections.

B. Liquidity Restrictions and Smart Money

One possible explanation for outflows inability to predict returns is that share restrictions impede the ability of current investors to act on salient information. If that explanation were correct, we should observe that outflows of funds with lower share restrictions are smarter than for funds with higher share restrictions.

To investigate this possibility, we rerun our performance prediction results. As before, the dependent variables are funds' cumulative style-adjusted returns for the 1-, 3-, 6-, and 12-month periods after the Form D filing. In addition, we include three share liquidity variables. *High Red.* is one if the fund's total redemption period, which is the sum of the advanced notice period and redemption period, is above the median redemption period (135 days). *Lockup* is one if the fund has a lockup period. *High Sub.* is one if the fund has a subscription period above the median value (30 days). We interact these liquidity variables with our flow variables to determine how share restrictions impact the smartness of investor flows. For the sake of brevity, Table IX only reports the coefficients for the interaction terms.

<Insert Table IX about here>

Our results indicate that the lack of performance prediction by outflows is not due to share restrictions. The coefficients on the interaction of flows with liquidity are generally not negative, meaning that funds with high redemption periods or lockups are not related to lower levels of predictability.

More importantly, we find strong, significant evidence that investors anticipate share restrictions. We find that inflows are much more predictive when redemption times are higher. Thus, investors are choosing to allocate money in the presence of high outflow restrictions only when they are very confident of future outperformance, which makes the restriction less binding. We find evidence consistent with this interpretation for both lockup periods and subscription periods as well. When a fund has a lockup period, an increase in new investors is more predictive of outperformance. Lockup periods only apply to new investors; thus, this restriction would affect new investors only. Finally, we find some evidence that investors anticipate inflow restrictions as well. Outflows from funds with high subscription periods, where it would be difficult to reinvest in the fund, are more predictive of future underperformance.[26]

C. Institutional vs. Non-institutional Investors

The inability of outflows to predict future performance could also be due to liquidity needs or tax considerations. Indeed, this is the hypothesis advanced by Keswani and Stolin (2008) for the mutual fund industry. Institutional clients, such as pension funds, however, should experience much less variation in liquidity needs than high net worth investors. Additionally, pension funds are not

[26] In untabulated results, we also investigate the impact of share restrictions on the ability of flows to predict fund death. We find limited differences, although high subscription periods make net flows less predictive of fund death. This is likely due to the overall impact of high subscription periods on flow allocation.

subject to taxes; thus, their outflow decisions should also not be related to tax considerations. Thus, if liquidity needs or taxes obfuscate the predictive power of outflows, we should see more evidence that institutional outflows are smart relative to non-institutional ones.

As previously documented, onshore and offshore U.S. hedge fund investors are very different. High net worth investors and family offices tend to use onshore fund investors while tax-exempt institutions such as pension funds are more likely to invest offshore. Thus, in this section, we separate our funds by domicile to example the smart money effect by clientele. Table X repeats our performance prediction tests including a dummy variable that is one if the fund is offshore and also an interaction term between this dummy variable and our flow variables. If liquidity needs were impacting the smart money effect, the interaction term should be positive and significant.

<Insert Table X about here>

Overall, we find that offshore flows are not smarter than onshore flows. Thus, our inability to find a smart money effect for outflows is not likely due to liquidity needs.[27]

D. High Water Marks and Smart Money

One additional feature of hedge funds that may affect the predictability of outflows is incentive fees. Unlike mutual fund that almost exclusively charge an asset based management fee, hedge funds typically charge a 20% performance-based incentive fee. Additionally, most funds have

[27] In untabulated results, we also perform these tests using investor concentration as our proxy for institutional ownership. We reach similar conclusions. We also examine the ability to predict fund death and find no difference between onshore and offshore investors.

a high water mark (HWM). Therefore, if a fund declines in value, future returns are exempt from incentive fees until the fund recoups those losses. This creates a rationale for staying in the fund.

To be concrete, assume for example that a hedge fund had a −10% return during the first year. Under these conditions, if this fund returns 10% gross of fees during the second year, investors will receive a net return of 10% due to the HWM. No incentive fee is paid. However, if after the first year the investor were to switch to another fund with the same performance of 10%, the investor would have to pay the incentive fee, leading to a net return of 8% only. As a result, investors may remain with funds below the high watermark, even if they believe they could underperform on a gross return basis, due to the incentive fee effect. This is especially the case if most of the absolute performance is driven by the strategy instead of alpha. This effect could reduce the smartness of outflows.

In practice, this effect cannot explain our findings. We repeat the previous analysis with an interaction term that is set to one if the fund is below its high water mark and zero otherwise and find no evidence that being below the high water mark alters outflows decision.

VI. Conclusions

Hedge funds investors are among the most sophisticated in the money management industry. We would therefore expect these investors to make smart investment decisions. However, hedge fund investors face hurdles when attempting to make money allocations. Hedge fund investments typically have inflow and outflow restrictions, which impede the ability of investors to react to information. Additionally, the hedge fund solicitation market is decentralized due to the lack of reporting requirements. Finally, hedge funds are extremely secretive about their strategies, which makes it difficult to evaluate portfolio managers.

In this paper, using the SEC's Form D to overcome prior data limitations, we evaluate the efficiency of hedge fund investment decisions. We first quantify the search costs that hedge fund investors face. Hedge fund solicitation, at least in the U.S., largely occurs outside commercial databases. Only approximately 17% of funds list themselves in commercial databases and only 15% of new investments take place in listed funds, which may make it difficult for investors to make "smart" investment decisions.

We use these new data to next examine the determinants of hedge fund investor decisions. We find that, based on current and past performance information, net flows have a linear flow-performance relation. However, only examining net flows does not fully reveal how investors make flow decisions. First, inflows, outflows, and the number of new investors are over twice the rate of net flows. Second, the net flow-performance relation hides convex relations between inflows and outflows and performance. Inflows and new investors have a convex relation to performance, similar to net flows for mutual funds. Outflows have a reverse convex relation with performance as the worst performing hedge funds experience higher outflows. This is in contrast to the mutual fund industry where there is no relation between performance and redemptions. Our findings suggest that hedge fund investors are better monitors, are less likely to suffer from the disposition effect, and are less likely to redeem due to liquidity needs.

With respect to future performance, we find that hedge fund net flows are smart. Even after controlling for performance persistence, net flows predict future performance and fund death. However, although hedge fund insiders likely hold a significant informational advantage, new investors and inflows are responsible for the smart money effect. The lack of smartness of outflows is not due to liquidity restrictions, liquidity needs, tax reasons, or fee advantages.

Finally, investors anticipate share liquidity restrictions when making investment decisions. Inflows are significantly more like to be smart when funds have outflow restrictions, indicating investors will only invest in illiquid funds when they are confident in future outperformance. We also find that outflows are significantly more likely to predict future bad performance for funds with inflow restrictions.

Overall, our results suggest that the sophistication of hedge fund investors is sufficient to overcome various headwinds when allocating capital.

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Table I: Sample Statistics for Form D Funds

This table presents summary statistics on our Form D sample from 2009 to June 2014 for the hedge fund industry, which includes funds self-reported in the subcategories of "Hedge Fund" and "Other Investment Fund." *No. of Filings (Funds)* is the number of unique Form D filings (funds). *Aggregate Sales (Investors)* is the total amount of aggregate sales (number of investors) based on the last filing of each fund. *Total New Sales (Investors)* is the total amount of new sales (investors) over our sample period. *Avg. (Median) No. Years Offered* is the average (median) number of years the funds have been offered for sale. *Avg. (Median) Total Sales (Investors)* is the average (median) aggregate amount of sales (number of investors) in the funds. *Avg. (Median) Min. Invt.* is the average (median) minimum investment across funds. *Avg. (Median) Yearly New Sales (Investors)* is the average (median) amount of new sales (new investors) during the year. *Avg. Yearly New Sales (Investors)* is the average amount of new sales (investors) as a fraction of the prior year's total sales (investors). Sales and minimum investment amounts are reported in millions of dollars ($MM).

	All	Hedge Fund	Other Investment Fund
No. of Filings	65,362	50,052	16,146
No. of Funds	22,803	16,569	6,234
Aggregate Sales ($MM)	6,000,500	3,260,780	2,739,720
Aggregate Investors	1,303,946	870,128	433,818
Total New Sales (2010 – 2014) ($MM)	3,271,480	1,408,400	1,863,080
Total New Investors (2010 - 2014)	399,034	263,558	135,476
Avg. No. Years Offered	12.2	11.9	13.2
Median No. Years Offered	3.9	4.2	2.4
Avg. Total Sales ($MM)	311.4	243.2	522.7
Median Total Sales ($MM)	38.51	39.84	33.00
Avg. Total No. of Investors	77.0	61.7	121.3
Median Total No. of Investors	17.0	18.0	16.0
Avg. Min. Invt. ($MM)	1.60	1.39	2.45
Median Min. Invt. ($MM)	0.50	0.50	0.20
Avg. Yearly New Sales ($MM)	112.4	58.9	359.0
Avg. Yearly New Sales (%)	68.0%	54.1%	134.2%
Median Yearly New Sales ($MM)	4.40	4.00	5.41
Avg. Yearly New Investors	13.7	11.0	26.2
Avg. Yearly New Investors (%)	7.09%	6.96%	7.55%
Median Yearly New Investors	2.0	2.0	2.0

Table II: Sample Statistics for Funds in Form D and Hedge Fund Databases

This table presents summary statistics on our Form D and hedge fund databases (DBs) matched sample. *No. of Filings (Funds)* is the number of matched Form D filings (Funds). *Filing (Fund) Match % (All/HF/Other)* is the Form D match rate for all Form Ds, Form Ds in the "Hedge Fund" subcategory, and Form Ds in the "Other" subcategory. *Aggregate Sales (Investors)* is the total amount of aggregate sales (investors) based on the last filing of each fund. *Total New Sales (Investors)* is the total amount of new sales (investors) over our sample period. *Avg. (Median) No. Years Offered* is the average (median) number of years the funds have been offered for sale. *Avg. (Median) Total Sales (Investors)* is the average (median) aggregate amount of sales (number of investors) in the funds. *Avg. (Median) Min. Invt.* is the average (median) minimum investment across funds. *Avg. (Median) Yearly New Sales (Investors) ($)* is the average (median) amount of new sales (new investors) during the year. *Avg. Yearly New Sales (Investors) (%)* is the average amount of new sales (investors) as a fraction of the prior year's total sales (investors). Sales and minimum investment amounts are reported in millions of dollars ($MM).

	All DBs	HFR	TASS
No. of Filings	14,581	12,940	7,702
No. of Funds	3,816	3,347	1,896
Filing Match % (All/HF/Other)	22.3/28.3/7.2	19.8/25.2/6.2	11.8/15.1/3.6
Fund Match % (All/HF/Other)	16.7/21.5/4.1	14.7/18.9/3.4	8.3/10.7/1.9
Aggregate Sales ($MM)	1,026,210	816,563	599,223
Aggregate Investors	286,147	255,119	173,533
Total New Sales (2010 – 2014) ($MM)	473,471	415,438	263,289
Total New Investors (2010 – 2014)	100,471	90,966	58,701
Avg. No. Years Offered	9.80	9.77	10.02
Median No. of Years Offered	6.24	6.27	7.19
Avg. Total Sales ($MM)	292.11	287.34	324.04
Median Total Sales ($MM)	57.58	57.65	68.90
Avg. Total No. of Investors	80.0	81.2	91.4
Median Total No. of Investors	34.0	36.0	40.0
Avg. Min. Invt. ($MM)	1.02	1.03	0.98
Median Min. Invt. ($MM)	0.50	0.50	0.50
Avg. Yearly New Sales ($MM)	57.92	57.18	58.24
Avg. Yearly New Sales (%)	51.12%	50.57%	48.66%
Median Yearly New Sales ($MM)	4.18	4.24	3.96
Avg. Yearly New Investors	12.3	12.6	13.2
Avg. Yearly New Investors (%)	25.54%	24.81%	24.87%
Median Yearly New Investors	2	3	2

Table III: Commercial Database Match Rate by Decile

This table reports commercial database match rates by deciles for Form D sales and investor characteristics. Each year we rank funds by their total historical sales (*Total Sales*), total historical number of investors (*Total Investors*), year over year change in *Total Sales* (*Inflows*), and year over year change in *Total Investors* (*New Investors*). We then split funds into deciles. For each decile, we calculate the average variable value (*Avg.*) and the match rate (*%*). We also report results for the top 2%, 1%, and 0.5% of funds. Sales are reported in millions of dollars.

	Total Sales		Total Investors		Inflows		New Investors	
Decile	Avg. ($MM)	%	Avg.	%	Avg. ($MM)	%	Avg.	%
1	0.06	9.5	0.00	8.5				
2	1.74	16.3	1.22	11.3	0.00	18.7		
3	6.30	20.1	3.25	15.6	0.02	23.3		
4	14.97	24.5	7.19	19.8	0.62	27.0	0.00	23.2
5	29.07	25.7	13.28	22.0	1.73	29.7	1.00	27.3
6	51.80	26.8	22.10	24.0	4.88	28.9	1.49	25.8
7	92.21	25.9	36.02	28.0	11.13	28.2	3.54	29.5
8	170.42	27.2	59.65	32.3	25.49	27.3	7.09	27.1
9	356.67	27.7	102.12	34.4	64.56	24.6	14.91	27.3
10	2,389.46	27.8	519.62	32.0	810.69	25.2	100.32	28.4
Top 2%	7,907.49	28.8	1,651.34	18.7	3,170.47	28.4	344.61	21.1
Top 1%	12,996.77	26.8	2,745.51	14.0	5,711.55	25.8	571.08	17.5
Top 0.5%	21,073.51	18.1	4,571.75	14.0	10,390.01	26.5	928.10	16.8

Table IV: Offshore vs. Onshore Matches

This table compares offshore and onshore funds filing Form D and reporting to commercial databases. Panel A reports the match rate of onshore and offshore funds by year and over the entire sample. Panel B compares statistics for matched onshore and offshore funds. *Min. Invt.* is the fund's minimum investment. *Total Sales* (*No. Investors*) is the total sales (number of investors) as of the last Form D filing. *Avg. Sale* is the average sale per investor while *Inv. Conc* is average percentage ownership. *Notice Period* and *Lockup* are the fund's redemption notice period and lockup period, respectively (in days). *Mfee* (*Ifee*) are the fund's management (incentive) fee in percent. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively.

Panel A: Match Rate by Year

Year	Onshore Funds	Offshore Funds
2009	39.0%	5.8%
2010	43.8%	6.7%
2011	44.1%	6.5%
2012	46.1%	6.8%
2013	46.1%	7.0%
Average	43.7%	6.5%

Panel B: Comparison of Fund Characteristics

	Onshore		Offshore			
	Mean	Median	Mean	Median	Diff	p-value
Min. Invt. ($MM)	1.56	1.00	3.55	1.00	-1.99	0.07*
Total Sales ($MM)	211.57	45.69	370.67	31.54	-159.10	0.00***
No. Investors	85.44	39.00	53.10	16.00	32.34	0.00***
Avg. Sale ($MM)	3.83	1.16	8.97	3.96	-5.14	0.00***
Inv. Conc. (5)	7.73%	2.44%	17.77%	5.56%	-10.04%	0.00***
Notice Period (days)	50.07	45.00	53.03	45.00	-2.96	0.01**
Lockup (days)	100.32	0.00	78.47	0.00	-21.85	0.00***
Mfee (%)	1.41	1.50	1.52	1.50	-0.11	0.00***
Ifee (%)	16.98	20.00	16.92	20.00	0.06	0.79

Table V: Net Flows, Inflows, Outflows, and Investor Changes

This table reports summary statistics on net flows, inflows, outflows, and investor changes. Net flows are computed using net asset information and account for organic asset growth. Inflows are computed as the change in total sales on consecutive Form D filings, indexed by the prior year's net asset amount. Outflows are derived from net flows and inflows. Investor changes are computed as the change in total investors using two consecutive Form D filings, indexed by the prior investor amount. Panel A reports these data by year whereas Panel B (C) reports the amounts based on concurrent (prior) performance quintiles, ranking funds within their styles. Reported values are equally-weighted averages.

Panel A: By Year

Year	Net Flows	Inflows	Outflows	Inv. Chg.
2008	3.41%	22.08%	18.93%	16.21%
2009	14.24%	34.37%	33.84%	49.44%
2010	14.54%	26.63%	24.25%	35.76%
2011	18.80%	31.02%	24.68%	46.05%
2012	17.26%	27.58%	24.96%	30.25%
2013	20.28%	30.25%	24.04%	29.69%
Average	16.46%	29.73%	26.35%	38.49%

Panel B: By Concurrent Performance Quintile

Quintile	Net Flows	Inflows	Outflows	Inv. Chg.
1-Low	1.2%	19.8%	27.1%	30.68%
2	8.6%	25.7%	25.3%	29.31%
3	14.7%	29.1%	25.6%	35.36%
4	24.8%	30.3%	24.5%	42.60%
5-High	28.6%	37.2%	27.0%	48.44%

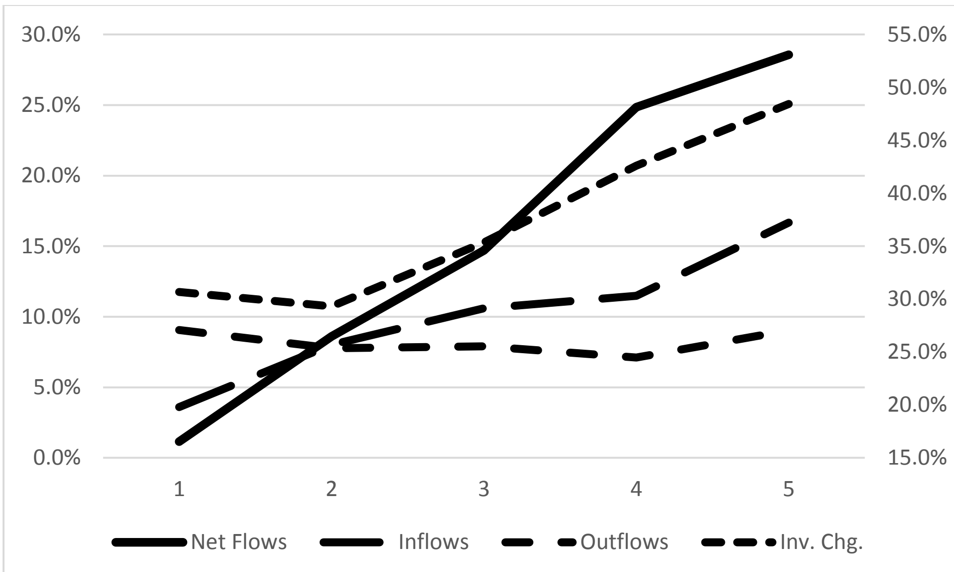
Panel C: By Previous Performance Quintile

Quintile	Net Flows	Inflows	Outflows	Inv. Chg.
1-Low	-10.2%	16.3%	30.1%	15.90%
2	3.4%	19.8%	24.4%	21.08%
3	7.5%	21.9%	25.3%	27.23%
4	16.1%	24.6%	23.4%	31.65%
5-High	27.2%	35.2%	23.9%	45.16%

Figure 1: Flow-Performance Relation

This figure plots the average investor flows across performance quintiles. Panel A plots the relation between flows and concurrent performance while Panel B plots the relation between flows and previous performance. Net flows are indexed on the left axis; inflows, outflows, and investor changes are on the right axis.

Panel A: Concurrent Performance



Panel B: Prior Performance

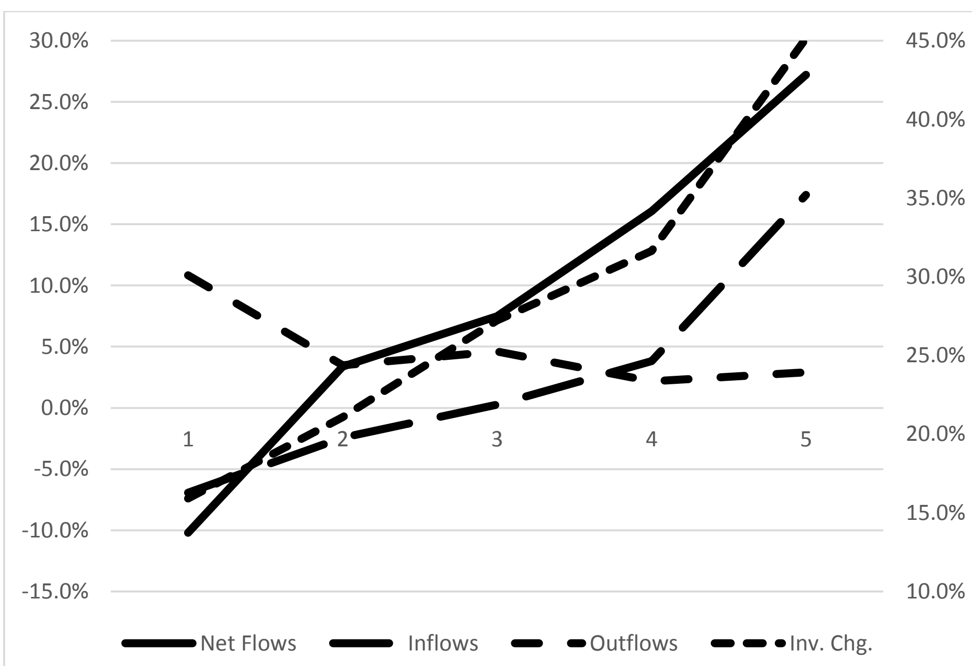


Table VI: Flow-Performance Relations

This table examines the relation between net flows, inflows, outflows, investor changes fund performance and characteristics. *Low Perf. Rank* and *High Perf. Rank* are piecewise-linear variables set at Min(*x*,50%) and Max(*x*-50%,0), respectively. Performance ranks are based on the concurrent year's performance in Panel A and the prior year's performance in Panel B. Both ranks are calculated relative to the fund's style. *Ret. Std. Dev.* is the return standard deviation over the prior 12 months. *Log(Net Assets)* (*Log(Investors)*) is the log of the prior net assets (number of investors) of the fund while *Log(Min. Invt.*) is the log of the fund's minimum investment. *Inv. Concentration* is average percentage ownership. *Management (Incentive) fee* is the fund's management (incentive) fee in percent. *High Watermark* is one if the fund has a high watermark. *Lockup, Adv. Notice, Red. Freq.*, and *Sub. Freq*. are the fund's lockup period, advance redemption notice period, redemption frequency, and subscription frequency in years. *Offshore* is one if the fund is domiciled outside the United States. *Style Avg.* is the flows average for the same style during the same period. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively. Standard errors are clustered by fund.

Panel A: Flow-Concurrent Performance Relation

	Net Flows		Inflows		Outflows		Investors	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Low Perf. Rank	0.321	3.87***	0.096	1.39	-0.100	-2.31**	0.040	0.34
High Perf. Rank	0.441	3.66***	0.257	2.89***	0.081	1.79*	0.456	3.29***
Ret. Std. Dev.	-3.366	-6.01***	-2.692	-6.70***	0.255	0.73	-2.369	-3.62***
Log(Net Assets)	-0.076	-6.56***	-0.077	-8.80***	-0.017	-3.50**	0.020	1.40
Log(Investors)	-0.048	-3.27***	0.002	0.18	0.014	1.82	-0.098	-3.96***
Inv. Concentration	0.065	0.47	0.075	0.79	0.056	1.02	1.445	4.88***
Log(Min. Invt.)	0.025	2.42**	0.018	2.27**	-0.001	-0.20	0.011	0.75
Management fee	0.077	2.68***	0.053	2.52**	0.015	1.14	0.113	3.39***
Incentive Fee	-0.001	-0.46	0.000	-0.04	0.000	-0.10	-0.002	-0.43
High Watermark	0.051	0.94	0.005	0.10	-0.028	-0.90	0.011	0.14
Lockup	0.008	0.34	0.016	0.91	-0.015	-1.44	0.037	1.32
Adv. Notice	0.110	0.58	0.149	1.13	0.086	1.05	0.181	0.71
Red. Freq.	-0.074	-1.14	-0.125	-2.55**	-0.050	-1.62	-0.141	-2.23**
Sub. Freq.	-0.115	-3.71***	-0.067	-1.63	0.031	1.24	0.057	-1.61
Offshore	0.005	0.14	0.035	1.13	0.075	4.66**	-0.192	-4.23***
Style Avg.	0.804	5.35***	0.826	5.95***	0.940	7.19**	0.711	6.88***
Nb. Observations	3,795		3,795		3,795		3,196	
Adj. R-squared	10.25%		8.38%		18.69%		4.84%	

Panel B: Flow-Prior Performance Relation

	Net Flows		Inflows		Outflows		Investors	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Low Perf. Rank	0.395	4.99***	0.113	1.79*	-0.099	-2.25**	0.130	1.44
High Perf. Rank	0.458	4.73***	0.310	3.90***	-0.016	-0.35	0.418	3.66***
Ret. Std. Dev.	-1.618	-3.95***	-1.374	-4.06***	-0.086	-0.31	-1.198	-2.50**
Log(Net Assets)	-0.053	-4.87***	-0.059	-7.08***	-0.015	-3.05***	0.046	3.57***
Log(Investors)	-0.038	-2.84***	0.007	0.65	0.009	1.15	-0.125	-5.53***
Inv. Concentration	-0.019	-0.13	-0.037	-0.34	-0.018	-0.30	0.497	1.89*
Log(Min. Invt.)	0.020	2.08**	0.016	2.01**	-0.001	-0.31	0.002	0.17
Management fee	0.070	2.62***	0.050	2.44**	0.016	1.19	0.094	3.11***
Incentive Fee	-0.001	-0.47	0.000	-0.19	0.000	0.32	-0.003	-0.90
High Watermark	0.047	1.00	0.012	0.29	-0.036	-1.19	0.048	0.81
Lockup	-0.008	-0.41	0.001	0.09	-0.014	-1.32	0.025	1.02
Adv. Notice	0.109	0.59	0.142	1.21	0.104	1.30	0.003	0.02
Red. Freq.	-0.004	-0.07	-0.068	-1.47	-0.050	-1.78*	-0.088	-1.58
Sub. Freq.	-0.116	-4.41***	-0.065	-1.81*	0.034	1.66*	-0.070	-2.45**
Offshore	-0.019	-0.55	0.029	1.03	0.069	4.25***	-0.138	-3.56***
Style Avg.	0.682	5.08***	0.682	5.28***	1.033	7.35***	0.519	5.94***
Observations	3,479		3,479		2,966		3,479	
Adj. R-squared	8.98%		6.17%		5.44%		12.22%	

Table VII: Prediction of Performance with Investor Flows

This table examines the prediction of fund performance. The dependent variables are the following year's 1-month, 3-month, 6-month, and 12-month cumulative style adjusted returns in percent. Panel A presents regressions with the fund's prior year performance rank within its style as well as our various flow measures. Flow and rank variables are in decimal format. Panel B presents regressions with dummy variables based on whether the fund is in the top, 2nd, or 3rd quartile as well as our various flow measures. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively. Standard errors are clustered by fund.

Panel A: Prediction using Performance Ranks and Investor Flows

	1-month		3-month		6-month		12-month	
	Coeff	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Perf. Rank	1.097	5.09***	1.112	2.87***	2.100	3.72***	5.129	5.09***
Net Flows	0.041	0.90	0.263	2.96***	0.396	2.97***	0.337	1.47
Perf. Rank	1.095	5.10***	1.157	2.99***	2.170	3.83***	5.186	5.16***
Inflows	0.090	1.40	0.261	2.07**	0.360	1.66*	0.324	1.02
Perf. Rank	1.071	4.95***	1.184	2.93***	2.477	4.02***	4.745	4.41***
Outflows	0.056	0.35	-0.217	-0.60	-0.403	-0.68	-0.883	-1.05
Perf. Rank	1.092	5.11***	1.208	3.10***	2.204	3.88***	5.352	5.29***
Inv. Chg.	0.014	2.00**	0.033	1.84*	0.041	1.88*	0.057	1.51

Panel B: Prediction using Performance Quartiles and Investor Flows

	1-month		3-month		6-month		12-month	
	Coeff	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
1st Quartile	0.744	4.46***	0.703	2.54**	1.511	3.60***	3.548	4.32***
2nd Quartile	0.550	3.69***	0.579	2.32**	0.774	1.98**	1.625	2.22**
3rd Quartile	0.378	2.60***	0.181	0.68	0.393	1.00	0.641	0.90
Net Flows	0.052	1.10	0.271	2.91***	0.404	2.96***	0.351	1.45
1st Quartile	0.743	4.46***	0.733	2.65***	1.559	3.70***	3.591	4.39***
2nd Quartile	0.551	3.70***	0.599	2.39**	0.803	2.03**	1.647	2.24**
3rd Quartile	0.376	2.59***	0.178	0.67	0.393	0.99	0.645	0.90
Inflows	0.097	1.46	0.270	2.04**	0.366	1.68*	0.334	1.05
1st Quartile	0.706	4.17***	0.687	2.24**	1.723	3.74***	3.180	3.67***
2nd Quartile	0.530	3.48***	0.875	3.18***	1.270	2.90***	2.021	2.55**
3rd Quartile	0.365	2.44**	0.369	1.29	0.714	1.65*	0.885	1.16
Outflows	0.055	0.35	-0.212	-0.56	-0.406	-0.67	-0.884	-1.01
1st Quartile	0.738	4.50***	0.767	2.74***	1.592	3.75***	3.747	4.55***
2nd Quartile	0.555	3.73***	0.617	2.44**	0.825	2.07**	1.692	2.28**
3rd Quartile	0.381	2.61***	0.201	0.74	0.424	1.06	0.682	0.95
Inv. Chg.	0.015	2.05**	0.034	1.84*	0.041	1.86*	0.058	1.49

Table VIII: Prediction of Fund Death with Investor Flows

This table examines the relation between fund death and net flows, inflows, outflows, and investor changes using a Cox Proportional-Hazard Model. *Net Flows, Inflows, Outflows,* and *Investor Change* are the prior year's net flow, sales, redemptions and changes in the number of investors, respectively. *Perf. Rank* is the performance rank of the fund within its style over the prior 12 months. *Ret. Std. Dev.* is the return standard deviation over the prior 12 months. *Log(Net Assets)* (*Log(Investors)*) is the log of the prior net assets (number of investors) of the fund; *Log(Min. Invt.*) is the log of the fund's minimum investment. *Inv. Concentration* is average percentage ownership. *Management (Incentive) fee* is the fund's management (incentive) fee in percent. *High Watermark* and *Lockup* are one if the fund has a high watermark and lockup period, respectively. *Adv. Notice*, *Red. Freq.*, and *Sub. Freq*. are the fund's advance redemption notice period, redemption frequency, and subscription frequency in days. *Offshore* is one if the fund is domiciled outside the United States. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively. Standard errors are clustered by fund.

	Model 1		Model 2		Model 3		Model 4	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Net Flows	-0.243	-3.78***						
Inflows			-0.227	-3.50***				
Outflows					0.078	0.79		
Investor Change							-0.129	-2.95***
Perf. Rank	-0.873	-6.98***	-0.896	-7.12***	-0.952	-7.21***	-0.906	-7.13***
Return Std. Dev.	0.379	0.24	0.397	0.24	1.827	1.13	0.518	0.32
Log(Net Assets)	-0.078	-2.14**	-0.102	-2.78***	-0.084	-2.06**	-0.096	-2.58***
Log(Investors)	-0.007	-0.12	0.023	0.39	-0.010	-0.16	0.008	0.14
Inv. Concentration	0.389	1.04	0.457	1.22	0.274	0.66	0.403	1.02
Log(Min. Invt.)	0.063	1.29	0.069	1.31	0.080	1.21	0.066	1.26
Management Fee	0.177	1.75	0.177	1.74*	0.140	1.38	0.193	1.90*
Incentive Fee	0.016	1.45*	0.016	1.45	0.013	1.21	0.015	1.36
High Water Mark	0.048	0.24	0.028	0.14	-0.004	-0.02	0.019	0.09
Lockup	-0.003	-7.13***	-0.003	-7.12***	-0.003	-6.80***	-0.003	-7.07***
Advanced Notice Period	0.000	-0.22	0.000	-0.13	0.000	-0.08	0.000	-0.17
Redemption Frequency	0.002	3.86***	0.002	3.74***	0.002	3.62***	0.002	3.69***
Subscription Frequency	-0.001	-0.63	-0.001	-0.62	-0.002	-0.68	-0.001	-0.60
Offshore	0.132	1.07	0.172	1.38	0.187	1.48	0.173	1.39
Nb. of Observations	3,812		3,812		3,210		3,767	

Table IX: Share Restrictions and Smart Money
(Coefficient on Flow Interacted with Liquidity Variables)

This table examines the effect of share restrictions on the smart money effect. The dependent variables are the following year's 1-month, 3-month, 6-month, and 12-month cumulative style adjusted returns in percent. Regressions include the prior year's performance rank within the fund's style and our flow measure, both in decimal format. We also include three share liquidity variables. *High Red.* is one if the fund's total redemption period (notice period plus redemption period) is above the median value (135 days). *Lockup* is one if the fund has a lockup period. *High Sub.* is one if the fund has a higher than median subscription period (30 days). We interact these share liquidity variables with our flow measures and report the values for the interaction terms. The other variables are omitted for brevity. ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively. Standard errors are clustered by fund.

Net Flows

	1-month		3-month		6-month		12-month	
	Coeff	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
High Red.	0.046	0.46	0.096	0.51	0.466	1.63	0.801	1.73*
Lockup	0.107	1.07	0.116	0.60	0.242	0.86	-0.535	-1.16
High Sub.	-0.153	-0.72	-0.232	-0.47	-1.033	-1.25	-1.786	-1.84*

Inflows

High Red.	0.321	2.47**	0.662	2.43**	1.368	3.14***	1.045	1.56
Lockup	0.081	0.60	0.135	0.50	0.231	0.53	-0.442	-0.66
High Sub.	-0.387	-1.20	-1.304	-1.91*	-1.350	-1.21	-2.944	-1.42

Outflows

High Red.	0.053	0.16	1.030	1.24	1.394	1.10	-0.469	-0.24
Lockup	-0.153	-0.46	-0.689	-0.83	-1.055	-0.86	-0.420	-0.21
High Sub.	-1.154	-1.49	-3.873	-1.97**	-2.403	-1.01	-5.346	-1.98**

New Investors

High Red.	0.038	0.79	0.079	0.92	0.246	1.60	0.118	0.48
Lockup	0.074	1.55	0.235	2.52**	0.408	2.97***	0.219	0.75
High Sub.	-0.375	-0.64	-0.945	-0.67	-1.711	-1.40	-6.719	-3.05***

Table X: Investor Type and Smart Money

This table examines the prediction of performance for different investor types. The dependent variables are the following year's 1-month, 3-month, 6-month, and 12-month cumulative style adjusted returns in percent. Regressions are run including the fund's prior year performance rank within its style and our variable flow measures, both in decimal form. Regressions also include an interaction term between our flow measure and a dummy variable that is one if the fund is domiciled outside the U.S. (*Offshore*). ***, **, and * represent significance at the 1%, 5%, and 10% levels respectively. Standard errors are clustered by fund.

	1-month		3-months		6-months		12-months	
	Coeff	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Perf. Rank	1.106	4.91***	1.136	3.25***	2.095	3.95***	4.991	4.80***
Net Flows	0.043	0.67	0.235	1.97**	0.373	2.25**	0.393	1.25
Offshore	0.083	0.88	0.163	0.87	-0.066	-0.23	-1.086	-2.23**
Flows*OS	-0.006	-0.07	0.077	0.41	0.073	0.25	-0.148	-0.31
Perf. Rank	1.104	4.92***	1.176	3.37***	2.161	4.06***	5.054	4.89***
Inflows	0.099	1.06	0.325	1.71*	0.436	1.40	0.329	0.75
Offshore	0.088	0.87	0.226	1.13	0.005	0.02	-1.105	-2.14**
Inflows*OS	-0.027	-0.21	-0.178	-0.73	-0.213	-0.55	-0.005	-0.01
Perf. Rank	1.102	4.99***	1.232	3.49***	2.197	4.11***	5.212	5.00***
Outflows	0.012	2.02**	0.031	1.80*	0.038	1.86*	0.051	1.45
Offshore	0.084	0.89	0.188	1.00	-0.053	-0.19	-1.130	-2.31**
Outflows*OS	0.021	0.55	0.031	0.50	0.072	0.77	0.159	0.96
Perf. Rank	1.078	4.80***	1.197	2.99***	2.455	4.14***	4.650	4.28***
Inv. Chg.	-0.066	-0.30	-0.415	-0.76	-0.682	-0.75	-1.125	-0.88
Offshore	-0.001	-0.01	-0.008	-0.03	-0.431	-1.07	-1.197	-1.74*
Inv.Ch.*OS	0.305	1.04	0.498	0.73	0.848	0.78	1.072	0.69