Are mutual funds sitting ducks?

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March 16, 2011

Abstract

Institutional capital is more patient than that of mutual funds. This provides an opportunity for institutions to profit from the predictable, investor flow-induced trades of mutual funds. In a sample of 3,623 13F filers not identified as banks, insurance companies or investment companies, and a subset of 491 identified hedge funds, we find that they do. In anticipation of a one standard deviation change in mutual flows into a stock, hedge funds trade 3 percent of quarterly volume in that stock. This effect is strongest in small and medium sized stocks and for mutual funds with more predictable trading. The tendency to predate is more pronounced in hedge funds that are better able to lock in investors' capital. Hedge funds earn abnormal returns when they trade on predicted mutual fund trades. A one standard deviation higher measure of predtatory trading is associated with a 0.9% higher annual 4-factor hedge fund alpha.

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1 Introduction

Hedge funds and mutual funds operate in the same market, but mutual funds are more constrained. Cash must be available for mutual fund investors to withdraw on short notice, and there are extensive limitations on which assets mutual funds can invest in, as well as portfolio disclosure requirements.[1] Hedge funds, which cater to more sophisticated investors, are free to choose their portfolios, leverage, and when to return capital to investors (see Teo (2011)).

While these regulations were meant to protect mutual fund investors, they may instead be harming them by making mutual funds too predictable. Brunnermeier and Pedersen (2005) show that *predatory trading*, "trading that induces and /or exploits the need of other investors to reduce their positions, is profitable. Prior work (e.g., Warther (1995); Berk and Green (2004); Coval and Stafford (2007); and Lou (2010)) shows that part of mutual fund flows are predictable. Berk and Green (2004) and Coval and Stafford (2007) show that front-running these anticipated trades by mutual funds can lead to significantly profitable returns.

Perhaps relatedly, hedge funds seem to earn abnormal returns which are the subject of considerable academic attention. Ackermann, McEnally, and Ravenscraft (1999) find that hedge fund returns are higher and more volatile than those of mutual funds. Fung, Hsieh, Naik, and Ramadorai (2008) provide an asset-based factor model to explain hedge fund returns. Aragon (2007) and Ramadorai (2011) relate hedge fund returns to illiquidity. Griffin and Xu (2009) find evidence against superior managerial skills in picking stocks whereas H. Li and Zhao (Forthcoming) find that manager SAT score explains part of the superior returns.

[1] In Feburary, 2004, the SEC required a registered management company to file its complete holdings with the Commission on a quarterly basis: "Enhanced Mutual Fund Expense and Portfolio Disclosure."

Aggarwal and Jorion (2010) find that newly created funds exhibit superior returns. Massoud, Nandy, Saunders, and Song (2011) find that hedge funds in loan syndicates short sell a firm's stock prior to public announcement of the loans, which raises concerns for conflict of interest by hedge funds. Agarwal, Daniel, and Naik (2009) show that "funds with a higher degree of managerial discretion, proxied by longer lockup, notice, and redemption periods, deliver superior performance." Perhaps, some of these excess returns to patient capital are related to mutual fund predation.

In this paper, we explore whether institutions, and hedge funds in particular, profitably trade on anticipated aggregate mutual fund flows. Since 13F filings only present long positions, we focus on the relationship between hedge fund's long positions and predicted aggregate mutual fund flows. Also, as 13F filings are quarterly, our focus on aggregate flows is different from the, likely higher frequency, Brunnermeier and Pedersen (2005) and Coval and Stafford (2007) type of predation of individual distressed funds.

We make several contributions to the literature. First, we show that institutions, especially hedge funds, trade on expected mutual fund flows. We find that hedge funds trade stocks in the same direction as that which is predicted by mutual fund flow for the next quarter, using past flows and mutual fund returns as predictors and assuming that funds scale their existing portfolios up or down in response to flows. In anticipation of a one standard deviation change in mutual flows into a stock, hedge funds put on trades worth 3 percent of quarterly volume. This type of anticipatory trading by hedge funds is stronger in mid- and small-cap stocks.

Second, we show that hedge fund flexibility is related to this predation. Hedge funds with more flexibility to lock up investor capital, as measured by longer redemption period and lockup period, are more likely to trade on expected mutual fund trades.

Third, we show that hedge funds profit from trading on predicted flows of mutual funds. These trades result in significant abnormal returns: a one standard deviation difference in hedge fund beta (with respect to predicted mutual fund flow) is associated with 0.9 percent annual return difference in hedge fund excess return. Given that our study captures profits from hedge funds' long positions and misses short positions, our estimate is most likely a conservative estimate of hedge funds' profitability from these types of trades.

Although predation is a pejorative term, we do not take a stand on whether this predation is beneficial to mutual funds, by providing them liquidity when they need it (as a store might prepare for the holidays by making sure more inventory is available), or whether hedge funds harm mutual funds by this practice. We do show that certain practices of mutual funds discourage predation, notably their propensity to disproportionately rebalance their portfolios in response to flows. If mutual funds strategically protect themselves in this way, this shows how both hedge funds and mutual funds interact to guard their interests in a competitive market.

The paper proceeds as follows. The following section presents the hedge fund and mutual fund data. The next section presents the construction of variables of interest and examines whether hedge funds trade on expected mutual fund flows. The following section examines whether hedge funds trade on predicted mutual fund flows. The next sections examine which stocks and which mutual funds are the most subject to these trades, and the last section concludes.

2 Data

2.1 Stock data

We gather stock prices, shares outstanding, and returns from CRSP. Specifically, we retain stocks with share codes 10 or 11 that are listed on NYSE, NASDAQ or AMEX. Average price during the period 2003-2010, our sample period, must be above a dollar and average market cap must be above 100 million. Details of the stocks in our sample appear in Table 1, Panel A.

2.2 Mutual fund data

The mutual fund data is from the CRSP Survior-Bias-Free Mutual Fund Database. This data includes mutual fund characteristics, returns, and portfolio holdings data since 2003. Summary statistics appear in Table 1, Panel B. Since we will work with 13F data which is at quarterly frequency, we create quarterly mutual fund returns and flows from the monthly data.

2.3 Institutional data

We use two sources of institutional and hedge fund data. The first is the 13F filings from the Thomson database of institutional holdings, also caled the S34 data set. This data set covers US equities and we focus on these in this study. The holdings are identified by CUSIP. Small holdings (under 10,000 shares or $200,000) are excluded from reporting requirements, as are certain cases where confidentiality is an issue. Investment companies must file a 13F quarterly if they manage more than 100 million in assets.

The 13F data has limitations. First, like the CRSP mutual fund holdings data, it presents quarterly positions and not trades. This is not a large limitation for this study because we are interested in positions set up in anticipation of an event (mutual fund trading) which will happen next quarter. Thus, we are interested in positions which are in place as of the end of each quarter in anticipation of the next.

Another limitation of the 13F data is that it presents only the long positions in equity and not short positions. To the extent that a filer has short positions in equities, we will miss part of their trading. A third limitation is that the data presented by Thompson does not include options or bonds. It is possible, for example, for a fund to have a small long position in a stock and a large effective short position due to its options holdings, and we would miss this. Fourth, 13F filers have the flexibility to request confidentiality of their holdings for up to one year although heavy paperwork is required and not all requests are approved. They must then file an addendum to the holdings when this right expires. Thus, the last year of data, 2010, has not yet been corrected for these holdings that remain confidential at the time of this writing.

The 13F files present several types of institutions. The type numbers are: 1: bank, 2: insurance company, 3: investment companies and their managers, 4: independent investment advisors, 5: all others. We select types 4 and 5 because these are the categories that could contain hedge funds will eventually have matches with TASS. There are 3,623 funds here from 2003 to 2010.

2.4 Hedge fund names, characteristics and returns

The second source of hedge fund data is the Lipper/TASS hedge fund database. This database provides monthly hedge fund returns and net asset values, along with many mutual fund characteristics, but no holdings. The first part of our study is based on all type 4 and

5 funds in Thomson, and later we use the subset of 491 funds that have been hand-matched by name with the TASS database.

We are conservative in our matching and have no doubt left out some matches. For example, would not match Schooner Asset Management, LLC (TASS) with Schooner Capital, LLC (13F), or SCM Advisors, LLC (TASS) with SCM Investments, LLC. (13F), but we would match Shah Capital Management, Inc with Shah Capital Management (TASS), and State Str Research & Mgt Co. (13F) with State Street Research & Management Company (TASS). Details of the hedge fund data appear in Table 1, Panel C.

3 Construction of variables

We would like to know whether hedge funds base their portfolio decisions on predicted mutual fund flows. To measure predicted mutual fund flows into each stock, we use a simple model that predicts flows for each fund. The prediction model is in the same spirit as Coval and Stafford (2007), who find that approximately half of the variation in mutual fund flows can be predicted with lags of fund returns and fund flows. However, the main difference is that we forecast aggregate, and not simply distressed, mutual fund flows. As in Coval and Stafford (2007), fund flows are defined as:

$$Flow_{m,t} = NAV_{m,t} - NAV_{m,t-1}(1 + R_{m,t}) \tag{1}$$

Where t indexes quarter, m indexes the mutual fund and NAV_t is the net asset value of the firm at the end of quarter t. This formulation assumes that all trades were made on the last day of the quarter, but a similar measure that assumes trades are made at the beginning of the quarter yields similar results. We regress total fund flows, on four quarters of lagged flows and four quarters of lagged returns.

We set up a simple prediction model for mutual fund flows, as follows:

$$\$\ \widehat{\text{Flow}}_{m,t+1} = \sum_{\tau=0}^{3} A_{m,t} * Flow_{m,t-\tau} + \sum_{\tau=0}^{3} B_{m,t} * R_{m,t-\tau} \tag{2}$$

Where the hat denotes prediction, m denotes the mutual fund, and R represents quarterly returns constructed by aggregating the three CRSP monthly mutual fund returns in each quarter. We estimate the coefficients $A_0 - A_3$ and $B_0 - B_3$ using OLS. We then use the coefficients to create fitted, predicted values of fund flows for each quarter Note that optimally, we only use past data to calibrate a true forecasting model. Thus, this this is in-sample forecasting. However, since we only have 24 quarters of data for each mutual fund at this point, we do not want to use up quarters in calibration.

In order to investigate whether our forecasting is effective, we examine correlations; the correlation between forecasted fund flows and actual fund flows is quite high, at over 80 percent. Figures 1 and 2 illustrate the ability of the model to forecast fund flows.

We would like to take the extra step of predicting stock-level fund flows, however. Coval and Stafford (2007) show that funds tend to adjust their entire portfolios proportionately in response to flows. We will assume that, in response to flows, the mutual funds buy or sell each stock in its proportions in their portfolio. Thus,

$$\widehat{\text{Stock flow}}_{m,i,t+1} = \$\ \widehat{\text{Flow}}_{m,t+1} * \text{Proportion of stock in portfolio}_{m,i,t}/\text{stock price}_{i,t} \tag{3}$$

Where i denotes the stock. This flow is in number of shares. We will later normalize by quarterly share volume as in Coval and Stafford (2007). Table 2 presents the correlation between predicted changes in share holdings by each mutual fund and actual share holdings. We then aggregate predicted changes in shareholdings over all mutual funds m to create a total quarterly predicted fund flow in or out of each stock.

Table 2 shows that the model is useful for predicting fund flows and stock flows. The correlation between predicted and actual fund flows as a percentage of TNA is 0.35. The correlation between actual and expected flows into stocks, which makes the extra assumption that funds will simply expand or contract their current portfolios, is 0.21. The correlation between actual and predicted stock level flows as a percentage of quarterly volume is 0.08.

4 Do institutions trade on predicted mutual fund flows?

4.1 Empirical model

We would like to know whether institutional, in particular hedge fund, portfolio decisions are related to our simple prediction of fund flows in and out of each stock. To investigate this, we calculate, for each institution in our larger Thomson 13F types 4 and 5 database, the change in holdings of each stock. Our model is the following:

$$\begin{aligned} \Delta\text{Institutional Holdings}_{h,i,t}/\text{Vol}_{i,t} = \quad & \alpha + \beta * E_t(\Delta\text{Mutual Fund Holdings}_{i,t+1})/\text{Vol}_{i,t} \\ & + \text{Control variables}_{h,i,t} \end{aligned} \tag{4}$$

Where h indexes the hedge fund, i indexes the stock and t indexes quarter. Control variables include the current quarters' total mutual fund holdings change, hedge fund total assets, and stock characteristics which are market capitalization, volume and quarterly return.

4.2 Implementation

Table 3 shows that predicted fund flows into stocks are related to hedge fund trades in the current quarter, even controlling for current quarter mutual fund trades, volume, and returns. The first two columns represent the whole sample of institutions with types 4 and 5, and the next two columns restrict the sample to the funds that match with our TASS hedge fund database.

In robustness tests, dividing by shares outstanding instead of quarterly volume or inserting Cusip and hedge fund fixed effects does not change the direction or significance of the result. Standard errors are clustered by hedge fund and quarter, but clustering by hedge fund manager instead does not affect the result.

The results are stronger for the TASS subset of the data, suggesting that hedge funds are more likely to trade in this way than other institutions of type 4 and 5. For our TASS hedge fund sample, one standard deviation difference in predicted aggregate mutual fund flows into a stock is associated with roughly $0.0132 * 0.0048 = 0.000064$ proportion of quarterly volume traded by each fund. Multiplying this by the number of funds in our sample, 491, yields over three percent of quarterly volume on average per stock. Thus, in anticipation of a one standard deviation change in mutual flows into a stock, hedge funds put on trades worth 3 percent of quarterly volume. This is is an economically meaningful quantity. While it is likely that hedge funds engage in both short and long position strategies, our test is limited to measuring only long position strategies. Hence, these results are conservative estimates of hedge funds' activity, and the actual trading activities are expected to be larger.

4.3 Which stocks do predators prefer?

Table 4 breaks down the results of Table 3 into three market capitalization categories: below 500 million, between 500 million and 3 billion, and over 3 billion dollars. The results are presented for the TASS subsample of hedge funds and are similar for the overall 13F fund types 4 and 5 sample. This table shows that the effect is strongest in small and medium sized stocks, and is not at all present in stocks above 3 billion dollars in market capitalization. These stocks are likely very liquid and it is difficult for hedge funds or mutual fund demands to influence their price.

5 Which hedge funds predate?

5.1 Hedge fund betas

In this section, we examine which hedge funds are likely to engage in the predatory strategy to exploit predictable movements in mutual fund flows. The variable of interest is the hedge beta with respect to expected mutual fund flows, which is a hedge fund-by-hedge fund version of the model in equation (4):

$$\begin{aligned}\Delta\text{Institutional Holdings}_{h,i,t}/\text{Vol}_{i,t} = \alpha_h + \beta_h * E_t(\Delta\text{Mutual Fund Holdings}_{i,t+1})/\text{Vol}_{i,t} \\ +\text{Control variables}_{h,i,t} \quad (5)\end{aligned}$$

The difference between models (5) and (4) are the h subscripts in α and β. As before, control variables are the current quarters' total mutual fund holdings change, hedge fund total assets, and stock characteristics which are market capitalization, volume and quarterly return. Hedge funds with fewer than ten holdings are excluded. We call β_h *Hedge fund* β.

Summary statistics of these betas appear in Table 5, Panel A. Since the betas represent individual hedge fund responses to aggregate mutual fund flows into stocks, they are small. Their mean is positive. Since there are some large values, these betas will be winsorized at the half-percent level on each tail in subsequent analysis.

5.2 Hedge fund betas and flexibility

In order to examine the impact of hedge fund flexibility in investment strategy, we divide the sample firms by their redemption period, which is the inverse of redemption frequency measured in the number of days between periodic redemptions dates allowed by the hedge funds. In case when a hedge fund has multiple products, we value weight the redemption frequencies of each product. We choose the redemption period cutoff of 91 days (1 quarter) because, the investment strategy considered in the previous section requires hedge funds to lock in their position for a quarter before the expected future movements of mutual fund flows. We expect hedge funds with redemption period longer than 91 days to be more likely to exploit the predatory investment strategy because these funds can accurately plan expected redemptions by customers and available funds for investment within a quarter. Hence, hedge funds with redemption period longer than 91 days are expected to have positive *Hedge fund* β. In contrast, those funds with redemption period shorter than 91 days are less likely to engage in predatory strategy and will have lower betas. As shown in Table 5, we find evidence consistent with this hypothesis: The mean of betas for hedge funds with redemption period shorter than 91 days are close to zero. In contrast, the mean *Hedge fund* β of hedge funds with redemption period longer than 91 days is 3.0 percent. Also, a two sample t-test shows that the difference in means of betas between these samples is statistically significant: hedge funds with redemption period longer than 91 days have on average 2.32 percent larger *Hedge* *fund* β than those with redemption period shorter than 91 days. We find similar results using lockup frequency as an alternative measure of the flexibility in investment horizon: *Hedge fund* βs are close to zero for hedge funds with lockup period shorter than 91 days, while the mean of *Hedge fund* βs are 1.7 percent for those with lockup period longer than 91 days. Panel C confirms the finding from Panel B in an OLS regression framework, where we find the parameter estimates of both redemption period and lockup period to be significantly positive. That is, hedge funds with more flexibility in investment strategy (longer redemption period or longer lockup period) have larger betas. To sum up, findings from Table 5 suggest that flexibility in hedge fund strategy (in the form of restrictions in redemptions by investors) allow hedge funds to engage in profitable trading strategies based on providing liquidity to mutual funds for their anticipated future trades.

5.3 Hedge fund returns

Is predation a profitable strategy? In this section we investigate whether hedge funds with higher *Hedge fund* βs earn higher returns. Since we wish to allow hedge funds to change their strategy over time, we calculate a quarterly hedge fund beta as follows:

$$\begin{aligned} \Delta \text{Institutional Holdings}_{h,i,t}/\text{Vol}_{i,t} = \alpha_{h,t} + \beta_{h,t} * E_t(\Delta \text{Mutual Fund Holdings}_{i,t+1})/\text{Vol}_{i,t} \\ + \text{Control variables}_{h,i,t} \end{aligned} \tag{6}$$

This equation is the same as (5) except that there are time subscripts for β and α. We rule out hedge funds with fewer than ten holdings. We winsorize these betas at the half-percent level on each tail in order to minimize the effect of outliers.

In Table 6, we regress hedge fund quarterly excess returns on their *Hedge fund* β in the prior quarter. Thus, if hedge funds were especially predatory in one quarter, they should have higher returns in the next quarter when mutual funds trade on their flows. The model is the following:

$$R_{h,t} - R_{f,t} = A_0 + A_1 * \beta_h + A_2 * (R_{h,t-1} - R_{f,t-1}) + A_3 * \text{Flow}_{h,t-1} + A_4 * SMB_t + A_5 * HML_t + A_5 * UMD_t + A_6 * (R_{m,t} - R_{f,t}) \quad (7)$$

where $R_{h,t} - R_{f,t}$ is the excess return on hedge fund h in quarter t, $R_{m,t} - R_{f,t}$ is the market excess return, SMB, HML, UMD are the Fama and French (1993) and momentum factors. We include lagged hedge fund return in the model, as Getmansky, Lo, and Makarov (2004), Bollen and Pool (2008) and Bollen and Pool (2009) find that the monthly returns of hedge funds are positively correlated, pointing to smoothing by hedge fund managers. Cassar and Gerakos (Forthcoming) show that intentional return smoothing by hedge fund managers is due to illiquidity in holdings. Since the holdings we are concerned with are quite liquid, we assume that their contribution to returns is not smoothed to a great extent. However, we include one lag of quarterly hedge fund return in our specifications.

Table 6 shows that, controlling for typical determinants of hedge fund returns and past hedge fund returns, betas are positively associated with hedge fund returns in the following quarter. Thus, when hedge funds buy in anticipation of mutual fund flows, they make abnormal profits. Hedge fund betas are not associated with hedge fund returns in the current quarter. A one-standard deviation difference in hedge fund beta is associated with a 0.64113*0.00341*4 = 0.9% annual return difference in hedge fund excess returns.

6 Which mutual funds are predated?

6.1 Mutual fund betas

To obtain a measure of how much a given mutual fund is predated upon in a given quarter, we aggregate the institutional flows into stocks and relate them to individual predicted mutual fund flows. We do not use actual flows because those could be affected by events that occur after the institutions have made their predictions.

$$\Delta\text{Institutional Holdings}_{i,t}/\text{Vol}_{i,t} = \alpha_{m,t} + \beta_{m,t} * E_t(\Delta\text{Mutual Fund Holdings}_{m,i,t+1})/\text{Vol}_{i,t} + \text{Control variables}_{h,i,t} \tag{8}$$

Notice that this model now aggregates over the h institutions but considers individual mutual funds, indexed by m.

6.2 Mutual fund betas and fund characteristics

Table 7 presents characteristics of mutual funds that we will relate to mutual fund betas. The first set of predictor variables describe how easy it is to predate each mutual fund. The first variable, Portfolio unpredictability, measures the departures from the expected expansion and contraction of the fund's original portfolio in response to flows. Thus,

$$\text{Portfolio unpredictability}_{m,t} = \sum_{i=1}^{N} \left(\frac{\text{Holding}_{i,m,t}}{TNA_{m,t}} - \frac{\text{Holding}_{i,m,t-1}}{TNA_{m,t-1}} \right)^2 \tag{9}$$

Another hedge fund measure is overall flow unpredictability:

$$\text{Flow unpredictability}_{m,t} = abs(Flow_{m,t} - Flow_{m,t-1}) \tag{10}$$

Where quarterly mutual fund *Flow* is in dollars and defined in (1). These measures only use one quarter lag to reflect that they might change over time.

A third measure, stock herfindahl, seeks to capture how widely held the securities in mutual fund portfolios are. We use the herfindahl index:

$$\text{Herfindahl}_{i,t} = \sum_{m=1}^{M} s_m^2 \tag{11}$$

where s_m is the fraction of stock i owned by fund m. If hedge funds tend target specific mutual funds, the coefficient on Herfindahl index will be positive (higer Herfindahls signal more concentrated ownership of the stock). If hedge funds tend to forecast aggregate flows, the coefficient on Herfindahl should be positive, meaning that mutual funds holding more widely held stocks will be predated more.

Other, more standard measures that might affect hedge fund predation of mutual funds are from the CRSP mutual fund database. They include fund fees, Log of total net assets, fund age since inception, turnover ration, whether the fund is retail fund. Summary statistics for these variables appear in Panel A of Table 7.

In panel B, these characteristics are regressed on quarterly fund betas. Standard errors are clustered by mutual fund and by quarter. The first column presents the coefficient on each variable when it is regressed by itself, and the second column presents all variables together. We find that the more unpredictable the fund portfolio is, the less it is predated by institutions. We also find that older funds tend to be predated more by institutions. For every additional year in fund age, fund beta is higher by 365*0.0312 = 11.4. This is perhaps a sign that institutions target individual funds rather than aggregate portfolios. As a fund gets older, if its strategy does not change it becomes more predictable as institutions learn about it.

6.3 Mutual fund betas and fund styles

Last, we ask whether mutual fund betas are related to fund style as defined by Lipper Class code from CRSP. Using the regression model from Panel B, we add dummy variables for the Lipper codes in our sample. As is apparent from Panel C of Table 7, our sample consists almost 30 percent of growth funds, 14.1% of growth and income funds, 11.3% mid-cap funds, and 17.7% small cap funds. The other types of funds are evenly spread across many categories. The regression in Panel C of Table 7 shows that telecommunications, small cap, mid-cap, industrial, health/biotechnology, consumer services, balanced funds are predated upon more than the others. This agrees with our results from Table 4 that show that our predation result is significant only for small and medium sized stocks.

7 Conclusion

In this paper, we show how hedge funds profit from the predictability of mutual fund flows. In particular, focus on anticipated forced trades of mutual funds as documented by Coval and Stafford (2007). In this setting, hedge funds with redemption period longer than a quarter are able to lock in their capital in stocks that are expected to be traded by mutual funds in the next quarter. Furthermore, we show that these front running strategies are profitable to hedge funds. A one standard deviation increase in the sensitivity of a hedge fund portfolio to predicted mutual fund stock flows is associated with a 0.9 percent higher annualized return.

Findings of this paper show how different actors in the market interact to exchange profits and settle prices. In our context, hedge funds exploit predicted mutual fund sales and make market prices efficient. In addition, our findings illustrate how illiquidity of funds contributes to profits of hedge funds. Namely, hedge funds that restrict redemption for at least a quarter are able to lock in their fund in a strategy to front run mutual funds which are subsequently forced to trade their shares in an anticipated way in the next quarter.

Further evidence whether hedge funds actively trade shares to manipulate prices of stocks that are anticipated to be traded mutual funds will be of interest for better understanding of price adjustment processes as well as for policy making purposes. We leave these exciting topics for future study.

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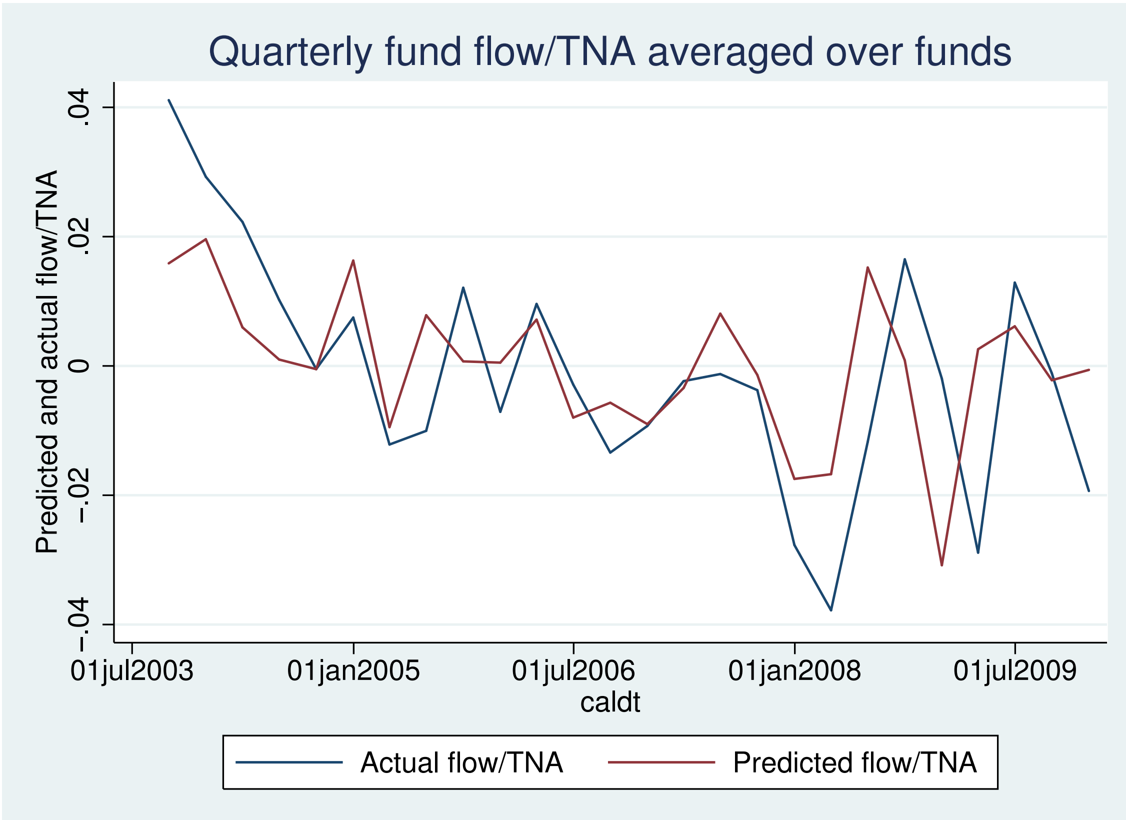

Figure 1. Quarterly actual and predicted flow divided by total net assets (TNA). This measure is averaged over all funds in the sample.

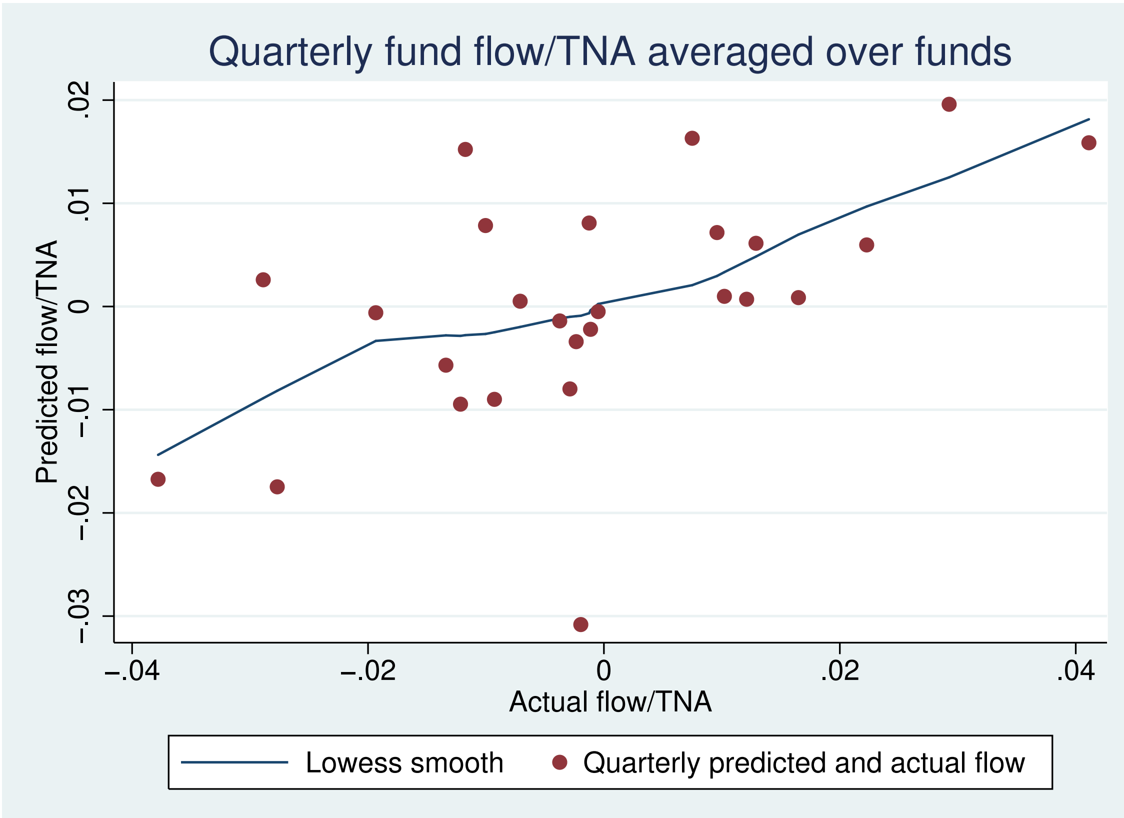

Figure 2. Quarterly actual vs predicted flow divided by total net assets (TNA).

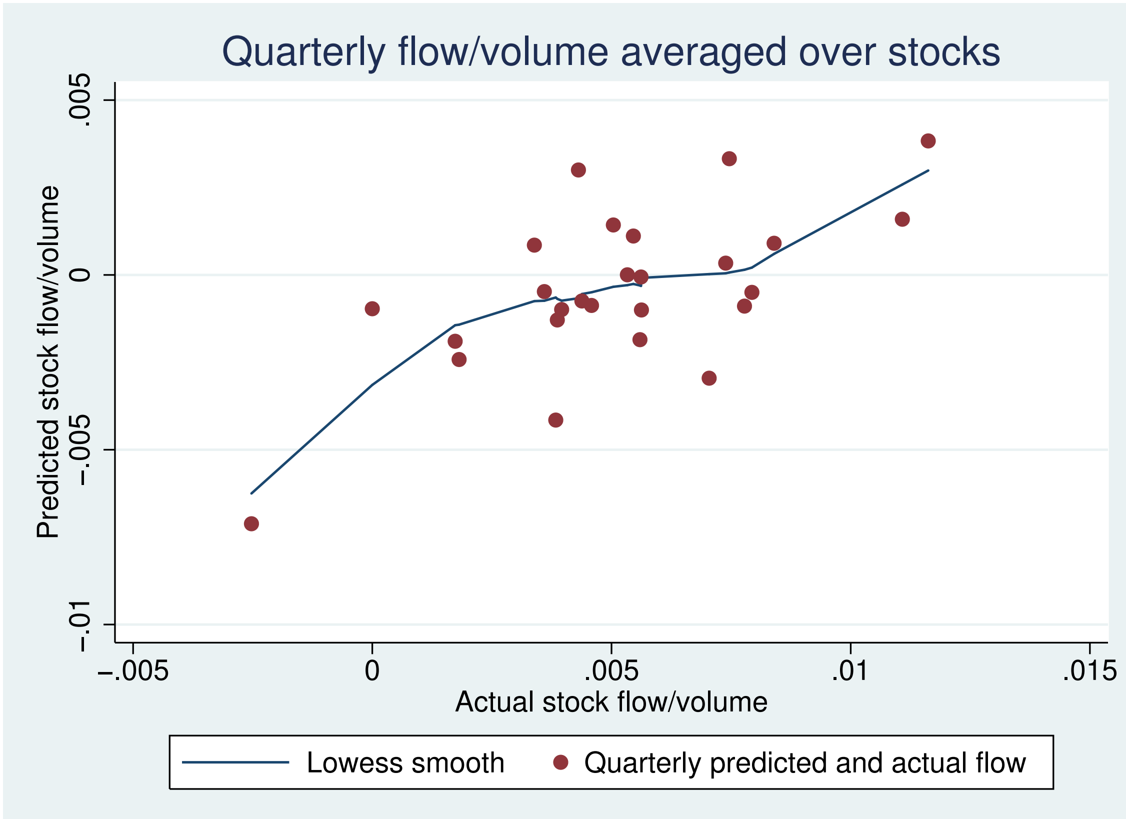

Figure 3. Quarterly actual vs predicted stock level flow divided by stock volume. This is arrived at by using the predicted flow and assuming that the fund will increase or shrink its portfolio in its current proportions.

Table 1 Summary statistics

Mutual fund owned is the proportion of the stock that is owned by mutual funds. *Quarterly volume* is in thousands of round lots. *Market cap* is number of shares outstanding times closing price at the end of the quarter, from CRSP. Mutual fund *Flow* at time t is $NAV_t - NAV_{t-1} * (1 + R_t)$ where NAV is net asset value and R is the fund return.

Panel A: Stocks.

Variable	Mean	SD	P1	P25	Median	P75	P99
Mutual fund owned	0.098	0.057	0.002	0.054	0.095	0.135	0.252
Market Cap (M)	4,678	16,566	68	450	1,000	2,766	69,346
Quarterly Volume	1,004	2,823	34	164	331	793	11,100

Panel B: Mutual Funds

Variable	Mean	SD	P1	P25	Median	P75	P99
Flow/TNA	-0.01	0.10	-0.31	-0.05	-0.02	0.025	0.34
Flow (Millions)	-6.36	357.41	-530.51	-15.26	-1.28	3.15	506
TNA (Millions)	1,610	6,603	2	59	230	875	27,142
Quarterly return	0.011	0.102	-0.271	-0.04	0.02	0.067	0.235

Panel C: Institutions

All 13F Type 4 and 5

Variable	Mean	SD	P1	P25	Median	P75	P99
Average # holdings	130.99	277.97	0	15.5	47.13	107.67	1646
Avg buys - sells (M)	18.79	337.89	-335.89	-4.31	-0.02	4.63	677.2811
Avg $ holdings (M)	2,376.16	17,081.93	1.27	77.42	189.96	693.52	42,013.99

Only the hedge funds in TASS

Variable	Mean	SD	P1	P25	Median	P75	P99
Average # holdings	117.98	233.77	0.33	12.96	34	105.9	1281.6
Avg. buys - sells (M)	17.82	144.1	-491.48	-5.75	0	9.87	835.67
Avg $ holdings (M)	2,449.44	11,501.52	1.87	67.34	215.70	927.29	53,640.64

Table 2

Predictability of mutual fund flows. Panel A presents in sample correlations between predicted and actual mutual fund flows, and predicted and actual stock flows from mutual funds. Panel B presents summary statistics.

Panel A. Correlations

Flow is total quarterly flow in dollars	All 13F types 4& 5	TASS only
$\text{Flow}_t/\text{TNA}_t$, $E_t(\text{Flow}_{t+1})/\text{TNA}_t$	0.567	0.562
Stock $\text{flow}_{i,t}/\text{vol}_{i,t}$, $E_t(\text{Stock flow}_{i,t+1})/\text{vol}_{i,t}$	0.060	0.080

Panel B. Summary statistics. Stock-level i subscripts omitted.

	Mean	SD	P1	P25	Median	P75	P99
Full Sample							
ΔIns. $\text{holdings}_t/\text{vol}_t$	-0.0002	0.0082	-0.0109	0.0000	0.0000	0.0000	0.0091
$E_t(\Delta \text{ MF holdings}_{t+1})/\text{vol}_t$	-0.0007	0.0048	-0.0123	-0.0024	-0.0006	0.0008	0.0134
$(\Delta \text{ MF holdings}_t)/\text{vol}_t$	0.0019	0.0359	-0.0428	-0.0042	0.0007	0.0070	0.0602
TASS Subset							
ΔIns. $\text{holdings}_t/\text{vol}_t$	-0.0002	0.0099	-0.0171	-0.0001	0.0000	0.0001	0.0143
$E_t(\Delta \text{ MF holdings}_{t+1})/\text{vol}_t$	-0.0006	0.0048	-0.0125	-0.0022	-0.0005	0.0008	0.0135
$(\Delta \text{ MF holdings}_t)/\text{vol}_t$	0.0020	0.0284	-0.0430	-0.0040	0.0006	0.0068	0.0607

Table 3

Regressions of institutional trades on predicted mutual fund flows. The dependent variable is stock-by-stock quarterly institutional change in holdings from 13F filings divided by total quarterly trading volume in that stock. Independent variables are aggregate predicted mutual fund change in holdings divided by quarterly volume. Quarterly volume is in millions of round lots. Market capitalization and stock returns are from CRSP. Standard errors are in parentheses and standard errors are clustered by institution and quarter. The first two columns represent the whole sample of hedge funds with fund type 4 and 5 in Thomson Reuters, while the following two columns represent the sample that has been hand matched by name with Lipper TASS. Stock, fund, or date dummies do not significantly affect the results. Stock-level i subscripts omitted.

	All type 4&5 13F Institutions		TASS hedge funds only	
	Δ Institutional holdings$_t$/vol$_t$	Δ Institutional holdings$_t$/vol$_t$	Δ Institutional holdings$_t$/vol$_t$	Δ Institutional holdings$_t$/vol$_t$
$E_t(\Delta$ MF holdings$_{t+1})$/vol$_t$	0.00717***	0.00567***	0.0147***	0.0132**
	(0.00209)	(0.00204)	(0.00527)	(0.00621)
Δ MF Holdings$_t$/vol$_t$		0.00230		0.00493*
		(0.00175)		(0.00295)
HF log(total assets)$_t$		6.00e-05***		4.60e-05***
		(1.76e-05)		(1.59e-05)
Stock Log(Market Cap)$_t$		-1.80e-05*		-4.78e-05**
		(1.01e-05)		(2.38e-05)
Stock volume$_t$(M)		4.93e-07		8.27e-07
		(3.96e-07)		(9.14e-07)
Stock return$_t$		0.000161**		0.000183
		(7.63e-05)		(0.000166)
Constant	0.000117***	-0.000818**	0.000164***	0.000162
	(2.79e-05)	(0.000402)	(4.64e-05)	(0.000426)
Observations	9,776,793	9,349,711	1,263,916	1,194,212
R-squared	0.000	0.002	0.000	0.001
Fund clusters	3,623	3,582	491	486
Quarter Clusters	26	25	26	25

Table 4

Which stocks have more predatory trading? Results in the last column of Table 3 (Confirmed TASS hedge funds only) are broken down by market capitalization. Market capitalization is the number of shares outstanding at quarter end multiplied by quarter end stock price from CRSP. Standard errors appear in parentheses and are clustered by quarter and hedge fund. Stock-level i subscripts are omitted.

	<500 Million Δ Institutional holdings$_t$/vol$_t$	500M-3B Δ Institutional holdings$_t$/vol$_t$	3B+ Δ Institutional holdings$_t$/vol$_t$
E_t(Δ MF holdings$_{t+1}$)/vol$_t$	0.0203*	0.0147*	-0.000720
	(0.0113)	(0.00807)	(0.00388)
Δ MF Holdings$_t$/vol$_t$	0.00660	0.0151***	0.00261
	(0.00431)	(0.00292)	(0.00202)
HF log(total assets)$_t$	4.59e-05	6.85e-05***	2.75e-05***
	(6.02e-05)	(1.60e-05)	(1.02e-05)
Stock Log(Market Cap)$_t$	-1.14e-05	-8.02e-05**	-4.41e-06
	(0.000142)	(3.29e-05)	(8.61e-06)
Stock volume$_t$(M)	-5.01e-05	-1.32e-05	-3.80e-07
	(3.26e-05)	(9.56e-06)	(3.86e-07)
Stock return$_t$	0.000272	0.000209	9.04e-05
	(0.000242)	(0.000187)	(9.98e-05)
Constant	-0.000439	0.000306	-0.000461
	(0.00220)	(0.000737)	(0.000287)
Observations	147,918	460,818	585,476
R-squared	0.001	0.003	0.001

Table 5

Panel A presents summary statistics on hedge fund betas. Hedge fund beta is the sensitivity of hedge fund stock position with respect to predicted mutual fund flow, and is defined in Section 4. Panel B presents the relationship between hedge fund expected mutual fund flow beta and flexibility in investment horizon as measured by redemption period and lockup period. Redemption period is the inverse of redemption frequency and is measured by the number of days between periodic redemptions dates allowed by the hedge funds. For example, annnual redemption frequency corresponds to 365 days of redemption period. Lockup period is the minimum number of months required to lockup the invested funds. Panel C presents results from OLS regressions of hedge fund betas and flexibility in investment horizon.

Panel A

Variable	Mean	SD	P1	P25	Median	P75	P99
Hedge Fund β	0.0106	0.6411	-2.2002	-0.0158	0.0006	0.0283	0.2581

Panel B

Variables	Redemption Period	Lockup Period
Period shorter than 91 days	0.0068	0.0038
Period longer than 91 days	0.0300	0.0171
Difference in Means	-0.0232* (-1.9519)	-0.0134* (-1.8124)

Panel C

	Dependent variable = Hedge Fund β	
Redemption Period	0.0001**	
	[0.000]	
Lockup Period		0.0011*
		[0.001]
Constant	0.0013	0.0044
	[0.006]	[0.005]
Observations	429	429
R-squared	0.011	0.008

Table 6

Betas and hedge fund returns. Excess hedge fund return is the quarterly hedge fund return minus the risk-free rate provided by Kenneth French's website. *Hedge fund* β is the sensitivity of the hedge fund's quarterly portfolio changes to aggregate changes in predicted next-quarter mutual fund flows. SMB, HML and UMD are the "small minus big", "high minus low" and "up minus down" return factors provided on Kenneth French's website.

	Hedge Fund Return$_t - R_{f,t}$	Hedge Fund Return$_t - R_{f,t}$
Hedge fund β_{t-1}	0.00346*	0.00341**
	(0.00182)	(0.00161)
Hedge fund $R_{t-1} - R_{f,t-1}$		0.00552
		(0.0479)
Hedge fund flow$_{t-1}$		0.0000
		(0.000)
SMB_t		-0.179**
		(0.0760)
HML_t		-0.177***
		(0.0482)
UMD_t		0.0498
		(0.0383)
$R_{m,t} - R_{f,t}$		0.151***
		(0.0427)
Constant	0.0142***	0.0156***
	(0.00)	(0.00)
Observations	3,544	3,502
R-squared	0.002	0.079
Quarter clusters	24	24

Table 7

Mutual fund characteristics and predation. Panel A presents summary statistics. Panel B presents regressions of Mutual fund β on various fund characteristics. Mutual fund β measures the sensitivity of the mutual fund portfolio to hedge fund predation. Portfolio unpredictability measures the sum of squared deviations in the prior quarter of the fund's portfolio changes from simple expansion or contraction of the portfolio. Fund flow unpredictability measures the average deviation of the mutual fund flows divided by TNA from that which is predicted by our prediction model. Herfindahl index measures the sum of squared percentages of ownership of each fund in our sample. Fund-level characteristics are from the CRSP mutual fund database. Standard errors are in parentheses and are clustered by quarter and mutual fund. Panel C presents, in a model with all of the variables in Panel B, additional dummy variables for Lipper mutual fund objective codes.

Panel A: Summary statistics. N= 21,330.

Variable	mean	sd	p1	p25	p50	p75	p99
Mutual fund β	-72.09	5372.96	-30958.07	-86.42	-0.48	74.34	30097.84
Portfolio Unpredictability	0.00	0.01	0.00	0.00	0.00	0.00	0.04
Flow Unpredictability	-18.09	2.75	-33.23	-18.61	-17.61	-16.76	-14.77
Herfindahl	0.10	0.05	0.03	0.06	0.09	0.13	0.25
Log(TNA)	9.78	2.37	4.55	8.20	9.72	11.34	15.64
Management Fee	0.71	0.31	0.07	0.528	0.71	0.89	1.68
Turnover Ratio	0.76	0.78	0.03	0.28	0.56	1	3.43
Index fund	0.01	0.08	0	0	0	0	0
Open to Investors	0.95	0.22	0	1	1	1	1
Retail Fund	0.62	0.49	0	0	1	1	1
Fund age (days)	3,234	2,630	121	1,422	2,703	4,194	14,085

Panel B: Regressions

	Alone Fund β	Together Fund β
Portfolio Unpredictability	-38,539**	-34,993**
	(16,076)	(15,508)
Flow Unpredictability	-14.35	-22.75
	(32.93)	(33.18)
Herfindahl	136.6	-232.5
	(519.0)	(600.9)
Log(TNA)	45.98**	22.30
	(18.77)	(25.89)
Management Fee	144.1	271.8
	(169.7)	(228.0)
Turnover Ratio	24.57	29.86
	(73.74)	(61.39)
Index fund	-1,389	-1,511
	(923.4)	(1,167)
Open to Investors	-34.33	14.12
	(63.77)	(75.55)
Retail Fund	-72.92	-163.4*
	(85.36)	(94.58)
Fund age	0.0311**	0.0312**
	(0.0145)	(0.0145)
Constant	-176.2***	-832.0*
	(66.14)	(444.2)
Observations	21,059	20,092
R-squared	0.000	0.003

Panel C: Lipper Class Codes.

Lipper Code	Lippper Objective	Regression Coef.	% of funds
B	Balanced Funds	920.1***	2.5%
		(148.8)	
BM	Basic Materials Funds	550.1**	0.0%
		(270.7)	
CA	Capital Appreciation Funds	273.0	4.1%
		(447.5)	
CS	Consumer Services Funds	981.0***	0.2%
		(82.54)	
EI	Equity Income Funds	358.6	3.8%
		(329.3)	
EMN	Equity Market Neutral Funds	14.72	0.3%
		(802.1)	
FS	Financial Services Funds	495.5	1.5%
		(347.5)	
FX	Flexible Portfolio Funds	406.3	2.9%
		(304.9)	
G	Growth Funds	394.8	29.3%
		(290.4)	
GI	Growth and Income Funds	278.0	14.1%
		(231.1)	
H	Health/Biotechnology Funds	409.4*	1.7%
		(209.1)	
I	Income Funds	710.0**	0.7%
		(301.3)	
ID	Industrial Fund	563.4**	0.3%
		(225.7)	
LSE	Long/Short Equity Fund	-405.2	0.5%
		(1,196)	
MC	Mid-Cap Funds	493.5**	11.3%
		(237.8)	
NR	Natural Resources Funds	459.6	1.1%

S	Specialty/Miscellaneous Funds	472.9	0.6%
		(301.8)	
SG	Small-Cap Funds	459.6*	17.7%
		(264.9)	
SP	S&P 500 Index Objective Fund	218.5	2.2%
		(556.2)	
TK	Science & Technology Funds	518.3	3.1%
		(403.5)	
TL	Telecommunication Funds	993.6***	0.7%
		(254.4)	
UT	Utility Funds	444.2	1.2%
		(298.9)	
		Total	99.8%