What Determines the Value of Assets Under Management?

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ABSTRACT

We address the heterogeneity of mutual-fund investors, in particular, its significance to the timing and circumstances of redemptions. We find that the inflows to top performers make these funds' future outflows more sensitive to their future performance, and we find that load funds attract investors more likely to remain, and less likely to respond to future performance. And a regime-shifting model that attributes inflows to either sensitive or insensitive investors helps determine the performance sensitivity of future outflows. From this model, we are able to estimate the value of a new dollar brought into a fund and relate this to the characteristics of the fund at the time.

1. Introduction

The academic literature on mutual funds has largely been concerned with the question of optimal investor choice. That is, which fund, if any, should an investor put his money in? But while this is an important question to answer, considering the number of consumers and dollars at stake, it is only one of the economically important questions about the industry. To practitioners, there is the similarly important question of *actual* investor choice. The number and variety of funds show that investors make a wide range of choices to invest in, remain in, and leave different funds. The livelihoods of these funds' managers depend on the future financial decisions of the investing public, particularly those investors who have made the choice to invest with them. In this paper, we address the heterogeneity of consumers' mutual-fund choices, with the goal of understanding what assets under management are worth to managers.

The challenge in addressing investor heterogeneity is that available data are aggregated across investors. Account-level databases such as those employed by Barber, Odean and Zheng (2004) and Johnson (2004) avoid this problem, but they contain limited, non-random samples of investors and funds, and so have limited ability to characterize the range of investor choices, and also, few researchers have access to such data.

One of the contributions of this paper is to propose and test a technique for estimating some of the variety of investors arriving at different funds, using only publicly-available, aggregated data. A regime-switching model serves this purpose because it allows us to embed our intuition that investors come in different types. While the variety of types is undoubtedly very wide, we keep it simple by focusing on one, potentially key, source of variation, which is performance sensitivity.

The main contribution of the paper is to document the economic significance of the variation of performance sensitivity and to value performance sensitivity in a meaninful way to managers. Previous research shows that some investors chase performance and others do not; we build on this finding by showing that investors carry their performance sensitivity with them into the future, making outflows of recent winners much more sensitive to their performance than the outflows of other funds. In other words, performance attracts new investment, but this new investment is less "sticky," and therefore worth less, than the money attracted by other funds.

Related work by Goetzmann, Ingersoll and Ross (2003) and Boudoukh, Richardson, Stanton and Whitelaw (2003) model the value of a fund using a contingent claims approach. While the Goetzmann, Ingersoll and Ross (2003) paper focuses on specific aspects of the hedge fund industry, the Boudoukh, Richardson, Stanton and Whitelaw (2003) paper models the value of a mutual fund given information about its inflows and outflows. As relates to this paper, one of the more interesting results of the paper by Boudoukh, et al, (2003) is that their model predicts that the sensitivity of the flow performance relationship affects fund value at least in a partial equilibrium model. While this result is economically intuitive, it lends additional credence to our goal of characterizing this sensitivity of investors and finding fund characteristics which will help identify different sensitivities across investors.

The goal of the paper is to in general identify whether there are significant differences in investor sensitivities to performance that can be identified using publicly available mutual fund characteristics. We start our analysis by first providing evidence of persistent behavior in how investors enter a fund and how they leave. This gives some evidence that if we can identify characteristics that help describe how an investor enters a fund—these same characteristics will help us predict their redemptions.

The second part of our analysis focuses on identifying the fund characteristics useful in segregating the inflows that are likely attracting performance sensitive investors versus insensitive ones. Performance at the time an investor enters a fund is one variable we consider. Graph 6 shows that high performing funds attract investors with greater sensitivity to past performance compared to low performing funds. Therefore, it seems past performance is a variable that will help in identifying investor types. Along this vein, Table 2 provides evidence of other fund characteristics that also identify performance-sensitive investors from the less-sensitive.

The problem with measuring investor sensitivity is we are trying to measure a quality that is not directly observable—it is proxied by the various mutual fund characteristics we mentioned above. Despite the unobservability, we need to statistically determine whether there are significant differences across investors that deserve modeling. To do this, we rely on a regime shifting model which infers from the data the unobservable distribution of investor sensitivities. We successfully identify two groups of investors: sensitive versus insensitive. For the first time, we can also statistically determine significant differences in how investors react between these two groups, suggesting that explicitly modeling investor sensitivity is an important area of future research.

The final thrust of the paper is to provide a framework for evaluating management companies. The stickiness of the investor base is directly related to the profitability of the management company. By drawing from the framework of impulse response functions, we regress current redemptions on lagged inflows. The coefficients on lagged inflows can be directly reinterpreted in terms of the value of assets to managers. For instance, a coefficient of 0.05 suggests that 5% of new inflows leave every month. We reinterpret the coefficients from our results in Table 3 in terms of the value to management and provide estimates of the expected fees. One key result here is we show as the lagged performance of the fund increases, the sensitivity of the asset base also increases which reduces the value of dollars attracted to the funds. This contrasts with the vast literature on flows where convexity in flows is thought to encourage risk-taking on behalf of the managers because of the value of new assets attracted to the fund. We find that new assets attracted to the fund when performance is high are worth less than when performance is low, dampening the affects of convexity. The results of the regime shifting model will provide an even more precise estimate of the expected fees earned by a management company. For a fund company looking to merge, this analysis will be immensely helpful in determining the dollar value of the newly acquired assets. For comparison, when we look at some proprietary data on mergers of fund companies, we find funds paid on average 3.3% of assets under management for a fund company. We find for an advisor charging 1.27% in expenses, assets should be worth approximately 2.54% of assets under management.

The rest of the paper is in three sections. Section 2 summarizes the data, Section 3 provides the analysis and regime shifting model and Section 4 concludes.

2. Data

To determine whether there is variation in investors' outflows that can be identified in their inflows, we need data that separates investors' inflows from their outflows. Account-level databases such as those employed by Barber, Odean and Zheng (2004) and Johnson (2004) are possibilities but they contain limited, non-random samples of investors and funds. These data also end in the late 1990s when returns were at their peak, so they do not reveal investors' behavior in a market downturn. Instead, we use publicly available data from the SEC N-SAR electronic filings covering 1995 to 2002. Matching these filings to the CRSP database is labor-intensive but it gives us a majority of funds in this time period, which includes both the bull and bear markets. Reuter (2004) also matches CRSP with N-SAR files but focuses on broker relations of mutual funds rather than the disaggregated flow data we consider here.

The N-SAR files are semi-annual reports. Some electronic filings are available as far back as 1993, but the complete sample is available starting 1995, when electronic filings became mandatory. In its report, each fund lists its individual monthly inflows and outflows over the past six months along with answers to various other questions about the fund operations over the same period.[1] Funds have some latitude as to which share classes to represent in a filing, so we make sure to match an NSAR to the correct share classes on CRSP, primarily by reference to fund name and total net assets.[2] If there

[1] An example of the N-SAR file questionnaire is available at http://www.sec.gov/about/forms/formn-sar.pdf. The individual data on inflows and outflows is provided in Question 28 (a)-(h).

[2] In this initial pass we were able to match about 86% of the ICDI numbers recorded in CRSP. Despite the high percentage of matches, there were several types of data errors and filtering that resulted in some data being thrown out. First, most of the analysis required at least 2 years of historical information so this restricts the sample immensely in terms of time observations (the sample of fund and time observations reduces by about 40%). Second, about 5% of the data was lost because of errors in reporting the correct scaling of flows. The SEC requires that flows be reported in thousands of dollars however some funds unknowingly report flows in dollars or in millions of dollars. There were other such scaling issues and

are multiple share classes, the variables are weighted by the total net assets in each shareclass—for example a fund with 50% in a class A with a 5% load and 50% in a class B share with a 5% load would report a 2.5% front-end load and 2.5% of a deferred load.

The matched sample of data we are reporting on in this paper only includes funds that are classified as aggressive growth (AG), large-cap growth (LG), and growth and income (GI). Because we collect data as it is reported, this data does not suffer from survivorship bias as we capture all the funds that reported after 1995 even if they ceased to report in later periods.

3. Empirical Analysis

Table 1 provides the summary statistics for the filtered dataset. We focus primarily on transactions in shares, rather than dollars, because this associates purchases and redemptions more directly. The overview shows only a modest increase in share redemptions in the down years of 2000 and 2001. Redemptions appear to level out in 1999-2001, although the dollar value of redemptions drops significantly due to the poor returns (see Graphs 1 and 2.). The average redemption rate was about 3-4% of total net assets monthly and this increased quite significantly from 1995 to 1999. The increase

because it was not consistent across funds or even across time for the same funds, we ended up dropping the entire time series of funds based on the following two criteria: (1) the reported monthly redemptions or inflows were on average more than 100% of the total net assets for the entire time period or (2) the reported monthly redemptions or inflows in one month over the entire time period was more than 200% of total net assets. The final more restrictive filter we use to identify funds exactly is to match the NAV reported in the N-SAR file with the NAV reported by CRSP. This reduces the sample by another 5% and leaves us with a sample we are certain is a true match. Unfortunately it also removes some valid data points where the NAVs may be off very slightly. For the analysis, we run the analysis on both sets of data and don't find large differences between the results.

indicates a decrease in investors' investment horizons, and accords with the recent statement by John Bogle that the average redemption rate is up to 41% per year.[3]

For comparison with the existing literature on fund flows (ie. Sirri and Tufano 1998 and Chevalier and Ellison (1997)), we present purchases, redemptions, reinvestment, and net flows as a function of relative performance in Graphs 3 and 4. We rank funds by their returns for each ICDI objective category (AG, GI, LG) in the current year (Graph 3) and in the prior year to their annual flows (Graph 4). The annual purchases, redemptions, and reinvestments are simply the aggregated monthly amounts over the year. Graphs 3 and 4 show a more linear relation between net flows and performance than the earlier studies fund. Purchases are sensitive to performance in the region of good returns, redemptions are sensitive in the region of bad returns, with the result that the difference is sensitive over the whole region

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3.A Commonality of inflows and outflows

Are there significant predicable differences in funds' redemptions? We start addressing this question by gauging whether the cross-sectional differences in funds' inflow patterns relate to the cross-sectional differences in their outflow patterns. In particular, we ask whether the funds whose inflows are more idiosyncratic, i.e., not explained by market inflows, also have more idiosyncrasy in their outflows. If they do, then we can conclude that different funds attract different groups of investors, where this difference carries implications for their eventual departure.

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[3] Discussion by Bogle on the stewardship quotient and shareholder stability. http://www.vanguard.com/bogle_site/sp20040105.html

We test this idea by first calculating two time-series correlations for each fund: the correlation of inflows to the fund with inflows to its category, and the correlation of outflows from the fund with outflows from its category. Then we test whether these correlations are themselves positively correlated, i.e., whether funds whose inflows are explained by market inflows also have outflows explained by market outflows. We calculate

$$Corr_i(Purchases, Mkt) = \frac{\sum_{t=1}^{T} \frac{1}{N}(Purchases_{i,t} - \overline{Purchases_i}) * (Purchases_{icdi,t} - \overline{Purchases_{icdi}})}{sd(Purchases_{i,t} - \overline{Purchases_i}) * sd(Purchases_{icdi,t} - \overline{Purchases_{icdi}})} \quad (1)$$

where $\overline{Purchases_i}$ is the average purchase for the fund over the full time period, $Purchases_{icdi,t}$ are the average purchases at each time period for each icdi objective category and $\overline{Purchases_{icdi}}$ is the average purchase made for each ICDI category across time, and we do the analogous calculation for redemptions. Graph 5 plots the pairs of correlations, and evidences a strong positive relationship between the two. To establish the statistical significance of this relationship, we regress one on the other (*t*-statistics in parentheses):

$$\begin{aligned} &\boldsymbol{Corred} = 0.197 + 0.286\boldsymbol{Cornew} + .644\boldsymbol{Shrout(Mils)} \\ &\qquad (23.25)\ \ (9.71) \qquad\quad (4.71) \qquad \boldsymbol{N} = 1223 \end{aligned} \quad (2)$$

The relation is significant, rejecting the hypothesis that idiosyncrasy in inflows does not explain idiosyncrasy in outflows. We now turn our attention to identifying the characteristics that will help quantify heterogeneity in investors' performance sensitivities.

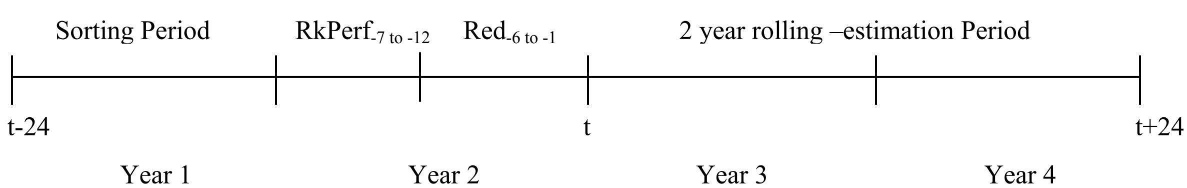
3.B Performance and future investor sensitivity

Our results suggest there are common characteristics defining how money enters a fund as well as how it leaves. The next questions are, what are these characteristics and do they help in identifying the sensitivity of investors? An intuitively important characteristic is sensitivity to past performance. Many studies, and also our results above, show that some investors, but not all investors, allocate to recent winners, and some investors, but not all investors, abandon recent losers. It seems therefore that the recent performance at the time an individual enters a fund would be a useful guide to how the same individuals will respond to performance in subsequent periods. Top performing funds are likely to attract performance-sensitive investors while low performing funds attract less sensitive investors who are entering, and intuitively will exit, the fund for reasons less related to performance. This is not to say that performance sensitivity is optimal or even sophisticated, just that it may be persistent.

We want to test whether good performance makes a fund's future outflows more performance-sensitive. To do this, we define a four-year window which we slide across our sample period, starting each January from 1994 to 1999. The first year contains the performance we sort on; those in the top 25% for their category (AG, GI or LG) are the HIGH funds, those in the bottom 25% are the LOW funds, and the rest are the MED funds. In the three subsequent years we measure, for each performance group separately, the sensitivity of six-month outflows to trailing six-month performance. So for example, we sort funds by their 1994 performance into HIGH, MED and LOW, and then for each HIGH fund we calculate its percentage outflows from July to December of 1995 and the rank (within its category) of its performance in January through June of 1995, and we regress outflows on performance rank. Formally, the regression model is

$$\%\Delta Red_{-1 \text{ to } -6} = \alpha_0 + \alpha_1 * \text{Lagged } RkPerf_{-7 \text{ to } -12} + \varepsilon \qquad (3)$$

We then move forward one month with the same set of funds, regressing their outflows in 7/95 through 12/95 on their performance in 1/95 through 6/95, and so on to the last regression of 7/97 through 12/97 flows on 1/97 through 6/97 performance. Thus, from each four-year window we get 25 cross-sectional regression coefficients for HIGH funds. We do the same thing for the LOW and MED groups of funds, and then we start the whole process over again with funds sorted on 1995 performance. So for LOW, MED and HIGH funds we get six sets of 25 regression coefficients, and our final step is to average across these six sets. The diagram below outlines the four-year window described above.



The 25 averages for HIGH and LOW funds are presented as time series in Graph 6. It shows that indeed, funds with higher past returns have greater performance-sensitivity in their outflows. All the way out to regression 16, which relates outflows from 22 to 27 months after the sorting year to performance in months 16 through 21 post-sorting, the cross-sectional coefficient for HIGH funds is below that of LOW funds. Eventually the lines converge, as would have to happen since subsequent relative performance must, by the same logic, re-sort investors across the funds.

Is the difference in Graph 6 statistically significant? To make this determination, we need a test statistic that addresses the overlaps in the data. We rerun the same regressions outlined above except this time nesting all funds in one model where funds that were presorted as low performers in the sorting year are identified with a dummy, LOW and the medium performers are identified with a dummy MED. The nested model takes the form

$$\%\Delta Red_{-1\text{ to }-6} = \underset{(26.12)}{0.0404} \; \underset{(-4.67)}{-0.059} * \text{Lagged RkPerf}_{-7\text{ to }-12}$$

$$+ \underset{(0.8687)}{0.0039} * \text{Lagged RkPerf}_{-7\text{ to }-12}*\text{MED} + \underset{(2.13)}{0.0232} * \text{Lagged RkPerf}_{-7\text{ to }-12}*\text{LOW} \quad (4)$$

Instead of providing estimates of 25 regression coefficients above, we simply determine whether the average coefficient for the LOW performers in the first year is significantly higher than high performers. Returning to our initial example, funds are sorted by 1994 performance. We initial regress the percentage change in redemptions from July to December 1995 on performance measured from January to June 1995. We role this regression forward 11 more times and take the average of each of the 12 coefficients. We repeat this for years 1994 to 1999 reporting the average of the coefficients for all years in equation (4) along with their estimated Fama-Macbeth t-statistics.

The estimates show that the low performing funds have significantly lower sensitivity to performance (-0.059 + 0.0232 = -0.0358) in the twelve months after their first performance ranking with a t-statistic of 2.13. This suggests that performance at the time an investor enters a fund may help in segregating sensitive from insensitive investors. A fund that performers well is likely to attract sensitive investors who respond more aggressively to changes in performance. We now turn to other possible variables that can help in segregating sensitive from insensitive investors and see whether this will improve our predictions of future redemptions.

3.C Variables predicting investor sensitivity and redemption behavior

Aside from lagged performance, are there other variables which might help explain the sensitivity of investors? One of the interesting choices investors make is whether to buy mutual fund shares through a broker or not. Bergstresser, Chalmers, and Tufano (2005) and Christoffersen, Evans, and Musto (2005) consider whether the presence of a broker changes the behaviour of investors and their sensitivity. Bergstresser, Chalmers, and Tufano (2005) consider whether a broker adds value to an investor based on several criterion such as performance and asset allocation and finds that on these criterion the broker doesn't seem to add value. Christoffersen, Evans, and Musto (2005) look more at the incentives of different types of brokers and find that in keeping with their incentives, in-house captive brokers reduce sensitivity by keeping investors in a bad performing fund while unaffiliated brokers more actively wake investors from poor performers.

For this reason, it might be interesting to explore whether brokers change the sensitivity of investors by extending the model of the previous section to incorporate the role of both brokers and performance. We take a regression model that explains current share redemptions with past performance and past share inflows, allowing for different sensitivities depending (as the previous section motivates) on whether past performance was strong or not, and we fit this model separately to load and noload funds. The coefficient relating lagged inflows to current redemption will provide an estimate of attrition rates of investors that will help us estimate future fees earned. The model is

$$\begin{aligned} ShrRed_t = {} & \alpha_0 + \alpha_1 * ShrNew_{-1\,to\,-12} * High + \alpha_2 * ShrNew_{-1\,to\,-12} * Med \\ & \alpha_3 * ShrNew_{-1\,to\,-12} * Low + \alpha_4 * Rk\,\mathrm{Re}t_{-1\,to\,-12} * High + \alpha_5 * Rk\,\mathrm{Re}t_{-1\,to\,-12} * Med \\ & \alpha_6 * Rk\,\mathrm{Re}t_{-1\,to\,-12} * Low + \alpha_7 * AvgShrOut \end{aligned} \quad (5)$$

where *ShrRed* are the shares redeemed in month t. *ShrNew* are the accumulated new shares attracted to a fund over the year (*months t-1 to t-12*) before the redemption is observed. *RkRet* is the ranked annual performance of a fund in comparison to its ICDI objective category for every period. *High, Med, and Low* are indicator variables which identify if a fund's ranked performance is in the top 20%, middle 60%, and bottom 20% of funds in months t-1 through t-12. *AvgShrOut* are the average shares outstanding in the fund over the past year.

Because we relate outflow decisions to earlier inflow decisions, we look at share numbers rather than dollar numbers. And we use annual new flows into a fund as an explanatory variable, even though we have monthly inflows, because the high autocorrelation of monthly numbers would introduce substantial multicolinearity. And because the sample periods overlap, we run a regression for each month across all years providing us with 12 estimates of each coefficient. The statistics reported in the table are an average of these 12 estimates along with an estimated t-stat for the average.

Table 2 provides regression results of equation (5) for various cuts at the data. The first column of Table 2 shows the overall attrition ranges from 5% to 8%. In other words, for every dollar attracted to a fund about 5-8% leaves every month. This attrition increases as the current performance of the fund worsens. There also seems to be convexity in redemptions where lower performance increases the sensitivity of investors to performance.

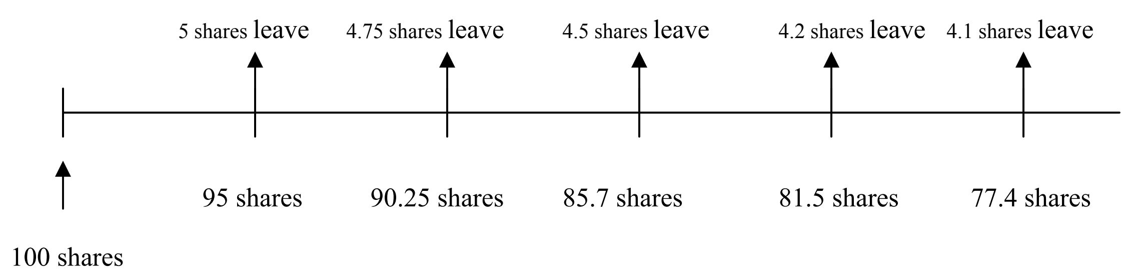
The first cut of the data divides funds into those with lagged rank performance above the median and below the median return within its objective category at each date. Lagged rank performance is measured over months t-13 to t-24 from the time that redemptions are measured. The regression results make a big distinction between money which is attracted to a fund when performance is high versus one where the performance is low. If one looks at a fund which had high performance in months t-13 to t-24 and then performed poorly, outflows of currently low performing funds relate more strongly to lagged inflows, ie. the coefficients α_3 and α_6 are considerably higher. This suggests that a new dollar flowing into a hot performing fund is much more likely to leave following subsequent poor performance.

In the next columns of Table 2, we split the sample into load and noload funds. Here there is evidence of more investor sensitivity in load funds than noload funds since the coefficients α_1 α_2 and α_3 tend to be higher for load funds. This findings corresponds to those of Christoffersen, Musto, and Evans (2005) that unaffiliated brokers increase the sensitivity of investor redemptions to past performance by 'waking' investors.

The remainder of Table 2 provides similar breakdowns by total net assets and by index fund. The results coincide with our intuition where a larger fund is more likely to have a subset of sensitive investors. There are several reasons for this intuition. First, smaller funds which have undergone a lot of attrition are likely to have lost their sensitive investors and retained their insensitivie investors (see Christoffersen and Musto (2002)).

Second, a larger fund may not have a close relation with investor base which makes it more susceptible to losing investors when performance deteriorates. Similarly, index funds tend to attract investors who are less sensitive to performance as one would expect. This group of investors has already decided it will not be able to outperform the market based on its own investment decisions. Hence, a performance downturn in the market should not result in the same outflow as one would expect for an actively managed fund. We should be clear to point out however that the investors in an index fund are not nearly as valuable as those in a load fund since these investors pay very low expenses and usually no loads. The index variable does seem to be one possible indicator of investor sensitivity to future performance.

The interesting outcome of our analysis in Table 2 is that the coefficients estimated on $ShrNew_{-1\ to\ -12}$ can be reinterpreted in terms of the value of investors to managers by the fees collected on the average dollar. For instance, suppose the coefficient on $ShrNew_{-1\ to\ -12}$ is 0.05. This would suggest the following pattern in monthly redemptions on average assuming the same attrition rate going forward.



From an evaluation perspective, the manager earning 1% on assets under management would earn one percent on 100 shares for 1/12 of the year, one percent on 95 shares for 2/12 of the year, etc. By the end of the year, 54 shares are left on which the manager earns the full one percent. We sum these time weighted fees and reinterpret the coefficients on $ShrNew_{-1\ to\ -12}$ in fees earned by the manager. The formula (asssuming a smooth continuous decline in the shares) relating the attrition coefficient to fees earned is

$$ExpFees = \frac{AnnualFee}{12} \times \left(-\frac{1}{Log(1 - AttrRate)} \right) \times 100 . \qquad (6)$$

For instance, suppose we estimated a coefficient or attrition rate of 0.05 for a fund charging 1% on its assets. In our example, this would imply an expected fee of 1.62% over the entire lifetime of a dollar attracted to the fund.

To conclude, Table 2 provides evidence of factors which will help us disentangle sensitive investors from insensitive ones. Still the question remains whether there is a significant difference between the sensitivity of investors in the various groups and whether there are significant differences in the heterogeneity between investors that are worth modeling. Analyzing the differences across investor groups as outlined in Table 2 is difficult because each fund will have different characteristics that define the sensitivity of its investor base. We've outlined four possible fund characteristics in Table 2 but we want to incorporate all these possibilities in one model so we can test the significance of the sensitivity of investors in one group versus another. The regime switching model in the next section provides a methodology of evaluating the impact of all these different indicators of investor sensitivity on the overall asset base of a mutual fund. It is a cohesive model and enables us to test whether there is a significant difference in the heterogeneity across investors and to identify the expected fees earned by a manager on a fund by fund basis rather than for a group of funds.

3.D Regime shifting model

The analysis until now has provided evidence of differences across investors in how they react to performance. The last section provided strong evidence of variables that would help separate sensitive investors from insensitive ones. The difficulty is of course identifying whether the sensitivities are significantly different across investors by modeling them in one model. Because we cannot observe directly the performance sensitivity of investors or a mutual fund, it is something we have to infer. We want to determine empirically whether there are detectable differences in investor behaviour across mutual funds that although not directly observed can be imputed from the data. We propose a regime shifting model.

Following the technique of Garcia, Lusardi, and Ng (1997), this econometric model infers from the data the unobservable distribution of performance-sensitivity across investors by placing a probability on each fund of a sensitive versus insensitive investor type. In Table 2, we segregated between groups in a one-dimensional manner with a fund either being sensitive or insensitive depending on its load structure or past performance, for example. Rather than taking one of the two extremes, the regime shifting model enables us to attribute a probability of being sensitive versus insensitive with a value ranging between zero to one. Formally the model estimates a probability of being either sensitive or insensitive as a logit probability,

$$P_{it} = \frac{\exp(\theta W_{it})}{1+\exp(\theta W_{it})} \tag{7}$$

where the probability is determined using variables that will help identify sensitive versus insensitive investors for each fund, *i*, and, *t*, observation. W_{it} is a set of variables describing the price sensitivity of a mutual fund's newly attracted investors. This would include the fund's size, lagged performance measured from months -13 to -24, an index indicator, and the percent of inflows subject to a load.

This probability weights two possible equations identifying redemptions for sensitive investors (equation 8) versus insensitive (equation 9) where the weight is P_{it} if the fund is considered sensitive and $(1 - P_{it})$ if the fund is insensitive.

$$R_{it+1}^{sens} = \alpha_{sens} + \beta_{sens} Q_{it} + \delta_{sens} z_{it} + \varepsilon_{it+1}^{sens} \tag{8}$$

and

$$R_{it+1}^{insens} = \alpha_{insens} + \beta_{insens} Q_{it} + \delta_{insens} z_{it} + \varepsilon_{it+1}^{insens} \tag{9}$$

Putting equations 7, 8 and 9 together, we arrive at the regime shifting model which is a nonlinear model estimated through maximum likelihood. The observed redemptions, R_{it+1}, are defined as the probability weighting placed on sensitive versus insensitive investors

$$f(R_{it+1}) = P_{it}^{sens} f(\varepsilon_{it+1}^{sens}, \phi_{sens}) + (1 - P_{it}^{sens}) f(\varepsilon_{it+1}^{insens}, \phi_{insens}) \tag{10}$$

The one difficulty in directly estimating the model is identifying what differentiates a sensitive investor from an incentive one. Our earlier results presented in Table 2 provide an example of some variables that will help identify investors whose redemptions will respond aggressively to performance and those that do not. Specifically we need to choose identifying variables z_{it} that distinguish between the two groups.

The logical candidate for z_{it} is to allow the two investor groups to incorporate lagged performance differently into their investment decisions. We define an insensitive investor as one whose dollar attracted to the fund leaves with the same probability, regardless of the fund's subsequent performance. On the contrary, a sensitive investor is one whose dollar attracted to the fund leaves at a different rate when performance is very low than when it is very high. Using the same model of redemptions that we used in the simple case of the previous section, equations (8) and (9) would more formally be written as

$$\begin{aligned} ShrRed_t^{sens} &= \alpha_{sens,0} + \alpha_{sens,1} * ShrNew_{-1\,to\,-12} * High + \alpha_{sens,2} * ShrNew_{-1\,to\,-12} * Med \\ &\alpha_{sens,3} * ShrNew_{-1\,to\,-12} * Low + \alpha_{sens,4} * Rk\,\mathrm{Re}\,t_{-1\,to\,-12} * High \\ &+ \alpha_{sens,5} * Rk\,\mathrm{Re}\,t_{-1\,to\,-12} * Med + \alpha_{sens,6} * Rk\,\mathrm{Re}\,t_{-1\,to\,-12} * Low \\ &+ \alpha_{sens,7} * AvgShrOut \end{aligned} \tag{11}$$

$$\begin{aligned} ShrRed_t^{insens} &= \alpha_{insens,0} + \alpha_{insens,1} * ShrNew_{-1\,to\,-12} + \alpha_{insens,2} * Rk\,\mathrm{Re}\,t_{-1\,to\,-12} \\ &+ \alpha_{insens,3} * AvgShrOut \end{aligned} \tag{12}$$

where $ShrNew_{-1\ to\ -12}*Med$ and $ShrNew_{-1\ to\ -12}*Low$ and $RkRet_{-1\ to\ -12}*Med$ and $RkRet_{-1\ to\ -12}*Low$ serve to distinguish the sensitive investors from the insensitive ones.

The results of the regime shifting model and the hypothesis test are provided in Table 3. In the probability equation, several variables appear to help segregate the data well. First, high lagged performance increases the probability of a sensitive investor as one would expect since money attracted to a fund which is currently doing well is likely to attract investors who will leave more quickly when returns falter. In terms of economic significance, this would suggest that a fund with a performance in the bottom 10% has a 8% chance of attracting a sensitive investor while a fund in the top 10% has a 20% chance of attracting a sensitive investor.

We also see that large funds are more likely to hold sensitive investors who respond more aggressively to poor performance. This is denoted by the positive and significant coefficient on TNA. In terms of economic significance, a $1billion fund has a 7% probability of a sensitive investor and a $20 billion fund has a 17.5% probability.

Statistically and economically, both TNA and lagged performance seem to be two variables that divide the sample into sensitive and insensitive investors.

From our earlier diagnostics, one would expect loads to be a significant factor in determining the sensitivity of investors and index funds to segregate a less sensitive group of investors. While the negative sign on the index fund indicator suggests that index funds are less sensitive, this variable is not significant. In addition, the negative coefficient on the percent of funds contrasts with our earlier diagnostics where a load fund was thought to increase sensitivity of redemptions to bad performance. Given the correlation between index funds and loads, it is likely that these two variables are interacting in the regime shifting model such that the significance of index funds in predicting insensitive investors is picked up in the load variable. It is should also be noted that the LOAD variable for the regime model is a continuous variable which measures the percent of inflows subject to a load where the size of the load may matter more and dissuade investors from leaving.   From an economic standpoint, these variables do not seem to be as important in terms of separating sensitive versus insensitive investors. For instance a fund with no money subject to a load would imply a 7% probability of a sensitive investor versus 6% for a fund with 50% of its money subject to a load. The model suggests that lagged performance and TNA are more economically important variables needed to separate sensitive versus insensitive investor bases.

In the sensitive redemption equation, our findings match what we would have expected. Larger new inflows result in larger redemptions and this is especially the case if the fund has recently performed poorly as denoted by the higher coefficient on *ShrNewy1*Low* than *ShrNewy1*High* in the sensitive investor regression. The coefficients on RkRet are generally negative and seem to be slightly higher on average in the sensitive equation than the insensitive equation.

The true test of our idea comes in comparing the two estimations of sensitive versus insensitive investors. Our hypothesis is that there is heterogeneity across investors in how they react to performance and we can identify this. If our hypothesis is true then the incoming flows of a sensitive investor must leave more quickly than the flows of an insensitive investor. In this framework, we can easily test this by testing whether

$$\begin{aligned} &H_0: \quad \alpha_{sens,i} = \alpha_{insens,1} \\ &H_A: \quad \alpha_{sens,i} > \alpha_{insens,1} \qquad \textit{where } i = 1,2,3 \end{aligned} \tag{13}$$

The attractive feature of modeling the sensitivity of investors in one model is that we can simply consider a typical t-test using the estimated covariance matrix from the maximum likelihood optimization to test the linear restrictions. Rejecting the null in favor of the alternative would suggest there are significant differences in investor sensitivity that can be identified. The results of the tests are provided at the bottom of Table 3. In all cases, the null hypothesis is strongly rejected suggesting there are measurable ways to identify heterogeneity across investors and these investor differences are important for predicting future fund flows and expected fees. We now turn to interpreting the model interms of the value of assets to managers.

3.E Interpreting the regime shifting model

We now want to see what kind of predictions this would imply in terms of the expected fees that a manager would expect for each fund. How much variation would this imply for the expected fees? We build on the intuition developed in Section 3C. The benefit now is that instead of having one regression to estimate the attrition rates for a group of funds (as used in Boudoukh, Richardson, Stanton and Whitelaw (2003)), this model identifies attrition rates on a fund by fund basis providing more precision for managers of fund. To identify the attrition rates for each fund we use the following equation,

$$AttrRate_{it} = P_{it}^{sens} \times (\alpha_1^{sens} * HI + \alpha_2^{sens} * MED + \alpha_3^{sens} * LO) + (1 - P_{it}^{sens})\alpha_1^{insens} \quad (14)$$

where HI, MED, and LO are simply indicators of whether the fund is in the top 20%, middle 60%, and bottom 20% of funds between months t-1 to t-12. From the attrition rate for each fund, we can then calculate the expected fees for the manager using equation (6) and the half-life of a dollar attracted to a fund is simply the number of years it would take for half of that dollar to disappear, or

$$HalfLife = \log(0.5)/(\log(1 - AttrRate)) * 12) \quad (15)$$

Table 4 provides averages of these estimated variables for the sample of funds in the estimation. The attrition rate ranges from averages around 3.89% and ranges between 2.68% to 9.37%. Based on an annual fee of 1%, these attrition rates correspond to an average expected fees of 2.12% ranging from 85bp to 3.07%. For the same annual fee, there is a significant in the range of values of a dollar attracted to a fund highlighting the value of this model.

The more interesting application of these results is to consider what implications the results of this model for flow convexity. It is well-documented in the literature that fund flows as a percent of assets are convex in performance. Several authors such as Chevalier and Ellison (1997) and Brown, Harlow, and Starks (>) discuss how this convexity alters the behavior of managers. All these models of behavior implicitly assume that the expected fees earned on new inflows is the same regardless of the performance of the fund. From our model in Table 3 and diagnostics in Table 2, it is evident that dollars attracted to the fund when performance is hot are less 'sticky' and less valuable. Hence, the desire to ramp up performance to increase the asset base may not be a strategic one if all the new money leaves as soon as performance sours.

Graph 7 provides a graph of how expected fees would be affected by performance. We calculate probabilities using equation (7) and the estimated coefficients. The ranked returns are assumed to range from 0 to 1 and increase by $1/10^{th}$. All other variables determining the probability of a sensitive investor are set to zero. Once probabilities are calculated attrition rates and expected fees are calculated. Graph 7 shows the expected fees for a fund that is *currently* performing well (top 20%) and a fund that is *currently* performing poorly (bottom 20%). What is notable about Graph 7 is that the expected fees drop significantly as the lagged performance of the fund increases. A dollar attracted to a fund during hot performance is worth less than during good performance.

We can try to quantify the economic and statistical significance of how much less these fees are worth by looking at Panel B of Table 4. Using the actual attrition rates and expected fees of each fund, we consider funds that were in the bottom 20% and top 20% before money arrived into the fund and calculate the average expected fees if these funds then were the bottom 20% and top 20% in the current year when money was attracted to the fund. From this, we see expected fees for a hot performing that subsequently did poorly would drop from 2.05% to 1.68% versus a low performing fund that subsequently did poorly whose fees would drop from 2.25% to 2.06%. What is notable is that a poor performing fund who would attract a dollar to their fund and continue to perform poorly would expect almost the same value out of that dollar as a fund which was performing well and continued to perform in the top 20%. This finding seems to negate the incentives of managers to improve performance so the important question is after controlling for the dollars attracted to funds at each performance level does the lower expected fee change the convexity relationship.

Graph 8 plots SHRNEWY1 multiplied by the expected fees calculated from the attrition rates assuming a 1% annual expense ratio. Essentially we are weighting the expected fees by the dollars expected at each ranked return level. The top line shows the expected relation between dollar inflows and lagged performance assuming expected fees are the same for each lagged return. The bottom line reflects the actual value of assets attracted to a fund which is currently performing in the bottom 20% of funds. It is evident that the positive relation between performance and inflows is dampened but not eliminated once accounting for the actual value and stickiness of the money.

4. Conclusion

(Need to include something on Part 3E and the convexity of flows)

We can teach consumers about making investment decisions, but can we learn about them from the decisions they make? A fund manager holds a portfolio of claims on fees from consumers, but these are not just any consumers, they are those consumers who chose his fund at particular times in the past. Managers undoubtedly know more about their shareholders than we know from their public disclosures, but even what we have should contain a wealth of information about the heterogeneity of funds investors, and this paper is a first attempt to unlock it.

We find that the money top performers attract is unstable, susceptible to flowing back out if performance disappoints. To put it another way, fund managers that have recently performed well face a stronger connection between their future performance and their retention of current assets. If managers perceive a connection between effort and future performance, this suggests they will respond with more effort.

We also find that the pathology behind purchasing B shares persists to future financial decisions. Investors in these shares are more likely to stick around, and less likely to respond to performance. One way to look at this is that investors cognitive biases are money in the bank for institutions in the position to monetize them, and B shares are the way to monetize fuzzy thinking about price schedules.

To capture the whole range of influences on investors' performance, we propose and test a regime-switching model, where the regimes are simply sensitivity and insensitivity. This delivers a statistically and economically significant boost to our prediction of redemptions, and provides a framework for future work on the actual economics of selling money management.

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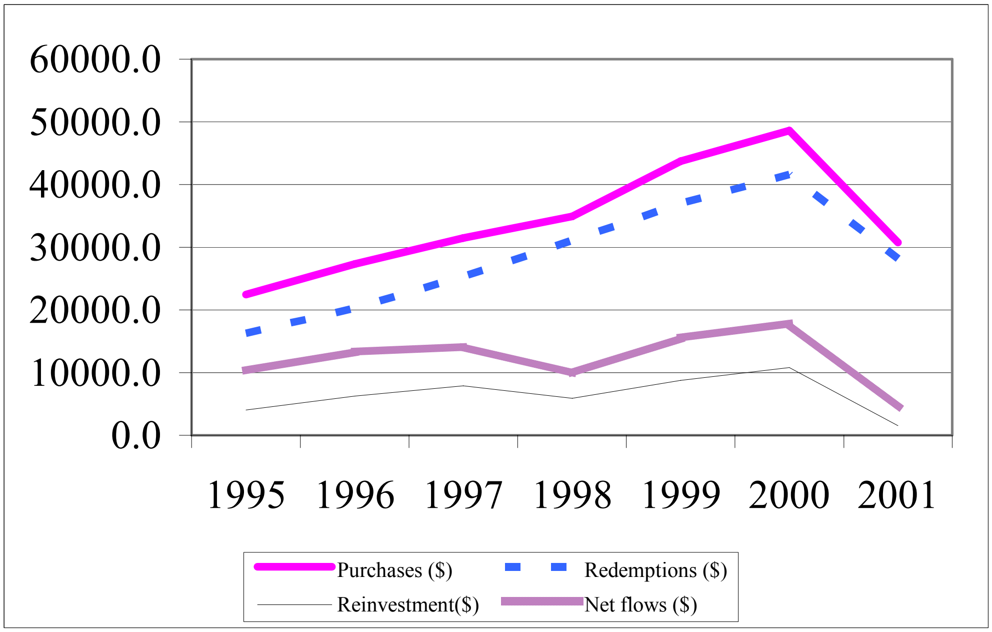
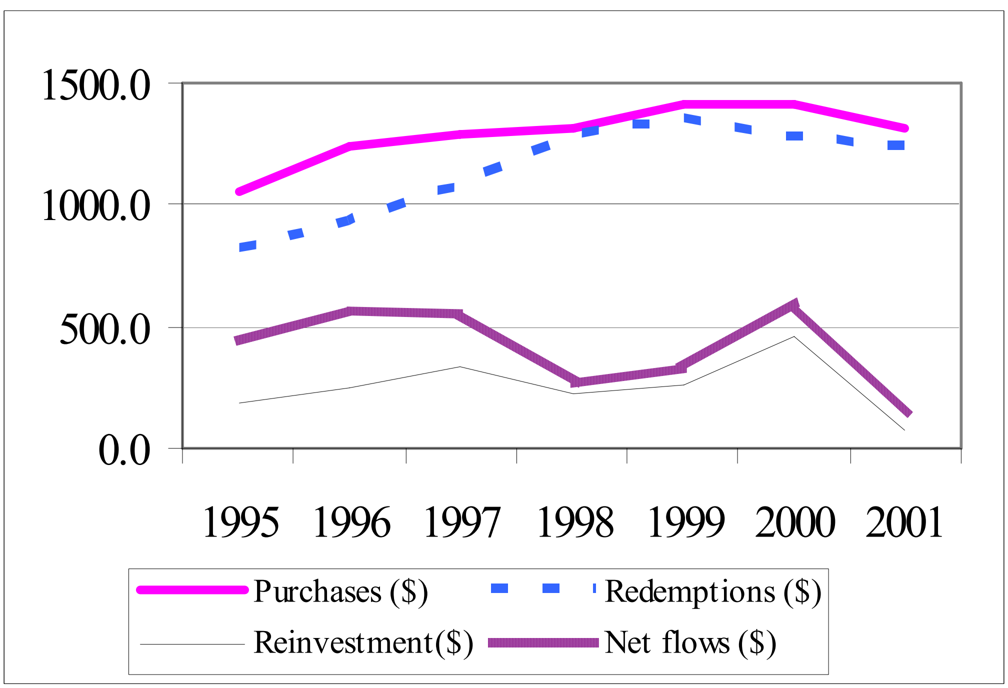
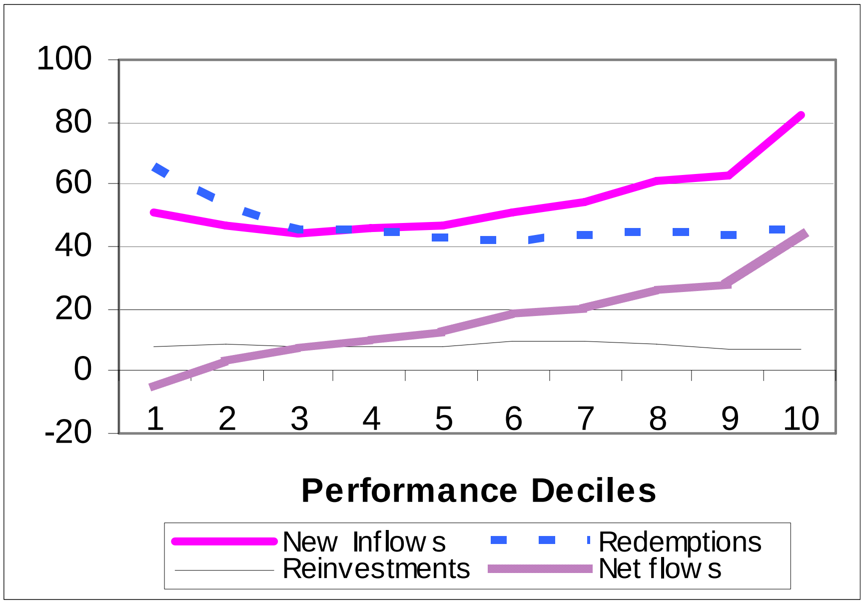


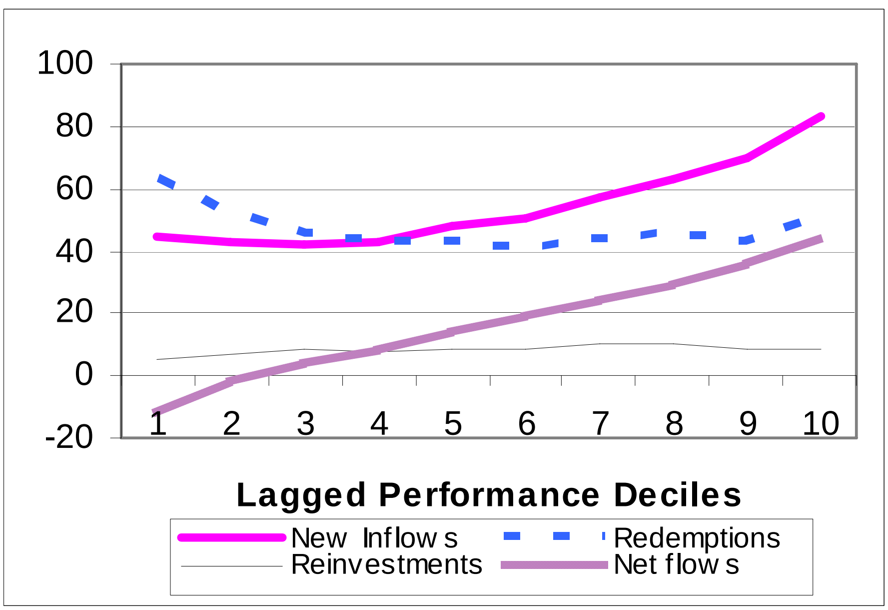
Graph 1. Annual dollar purchases, redemptions, reinvestments 1995-2001.
Units are evaluated in thousands of dollars annually.



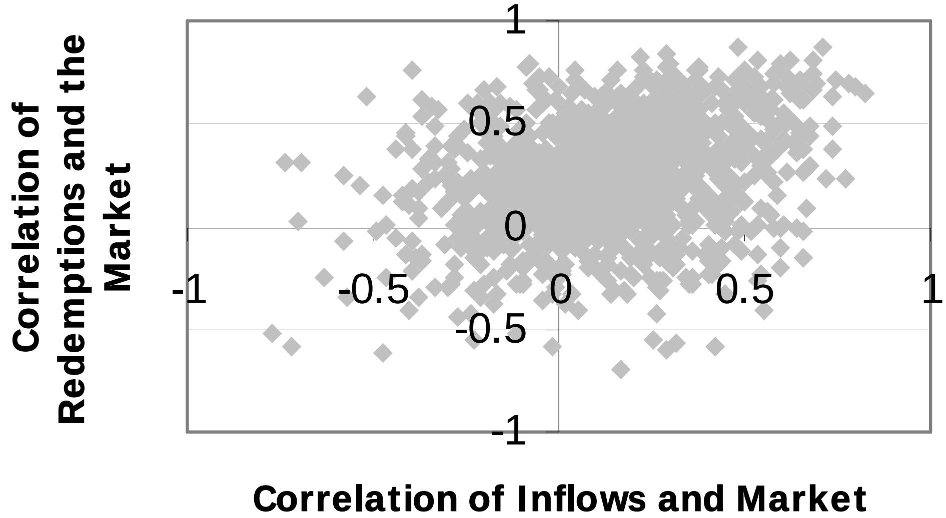
Graph 2. Annual shares purchased, redeemed, reinvested 1995-2001. Units are evaluated as '000s of shares annually.



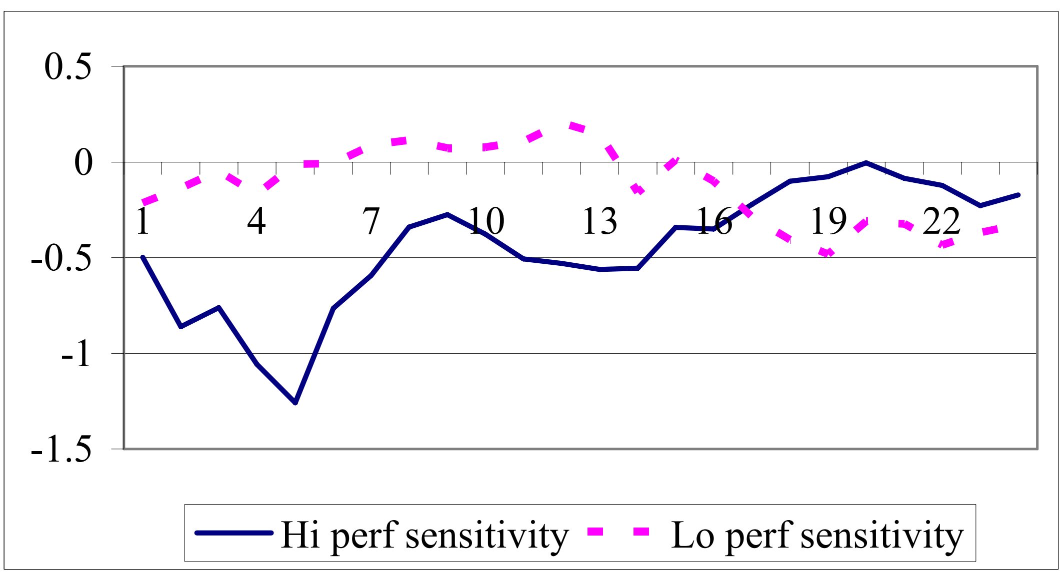
Graph 3. Percentage new flows and current performance. This graph plots annual new inflows, redemptions, and reinvestments as a percent of total net assets by the concurrent performance decile. Performance is evaluated over the same year as inflows and ranked by objective category.



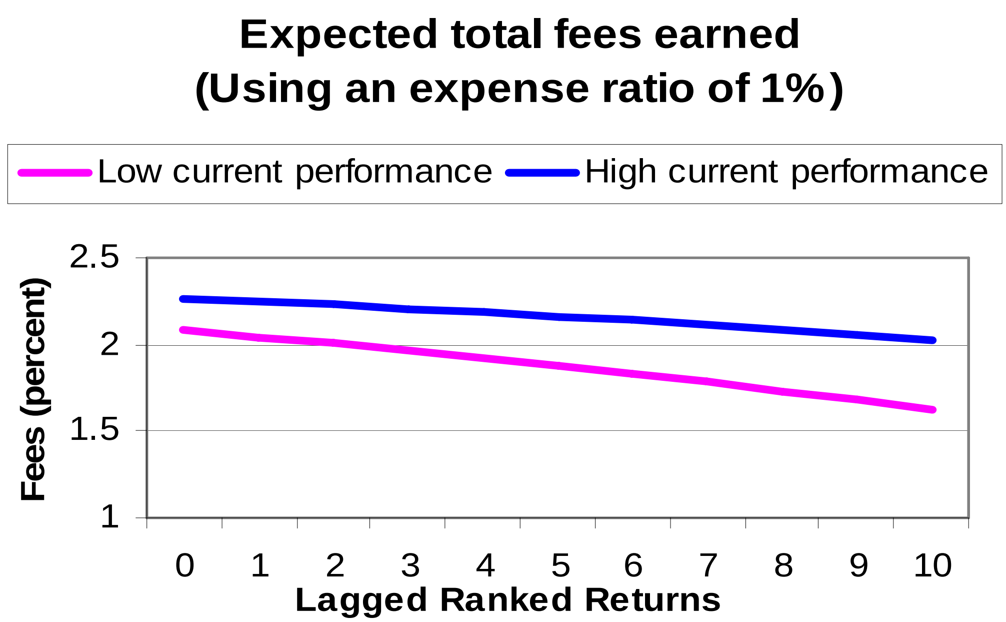
Graph 4. Percentage new flows and lagged performance. This graph plots annual new inflows, redemptions, and reinvestments as a percent of total net assets by the lagged performance decile. Performance is evaluated over the year prior to inflows and ranked by objective category.



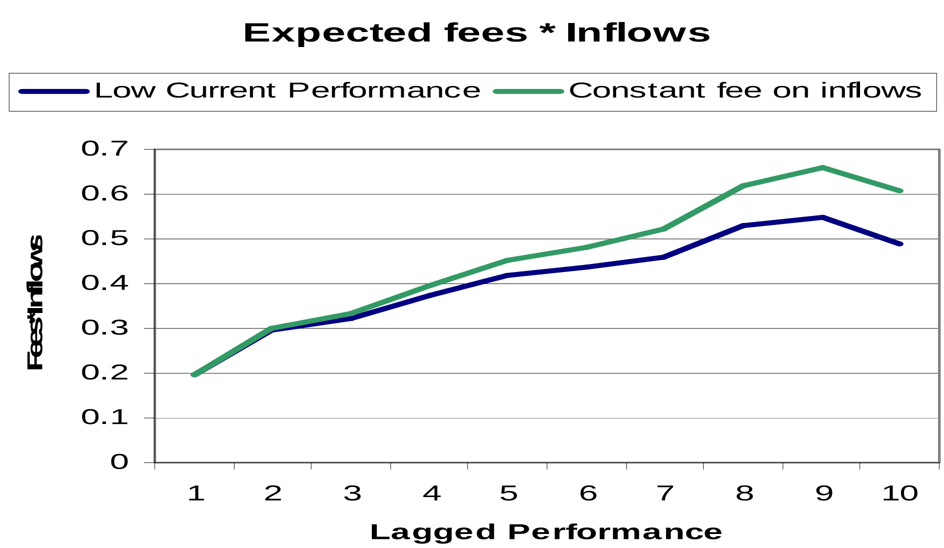
Graph 5. Correlation of inflows and outflows to the market. This graphs the correlation of inflows with the overall market and redemptions with the overall market redemptions by each icdi objective category.



Graph 6. Performance sensitivity over time. This graphs plots the regression coefficients of the percentage change in redemptions (for the 6 month period t-1 to t-6) on lagged performance (t-7 to t-12). The sample is divided based on the ranked performance in the period prior to estimation (t-13 to t-24) where high represents the top 25% of funds and low represents the bottom 25% of funds. This group is held constant while the regression is rolled forward a month for 24 months after the initial estimation period.



Graph 7. Estimated total fees by performance. This graph takes the estimated coefficients provided in Table 3 and converts them into expected attrition rates and expected fees for each fund using a base expense ratio of 1%. The bottom line relates the lagged ranked performance to average expected fees earned for a fund which is currently performing in the bottom 20% of funds. The bottom line relates the lagged ranked performance to average expected fees earned for a fund which is currently performing in the bottom 20% of funds.



Graph 8. Estimated dollars earned in fees. This graph takes the estimated coefficients provided in Table 3 and converts them into expected attrition rates and expected fees for each fund using a base expense ratio of 1%. The expected fees as a percent of net assets are multiplied by the new inflows into a fund to get the expected dollars earned in fees by a manager. The green line assumes that the expected fees are the same as those for a fund in the bottom decile.

Table 1. Descriptive Statistics

This table provides descriptive statistics of our matched sample of CRSP and N-SAR files from 1995 to 2001. These only include equity funds classified as either AG, LG, or GI according to the icdi objective cateogories in CRSP. The purchases, redemptions, and reinvestments are based on information from Question 28 (a) – (h) in the NSAR file. Although approximately 86% of the CRSP data was initially matched with the NSAR files, this sample has been filtered because of data entry errors in the N-SAR files. First, we eliminate those funds where the average redemptions or average purchases for a fund are more than 100% of total net assets. We also eliminate the entire history of data for funds where the redemptions or purchases were more than 200% of total net assets at any point in time. Finally, we also require that the NAV listed on the N-SAR file match the NAV listed in CRSP. Panel A provides the annual summary statistics while Panel B provides the monthly statistics for the same time horizon. All values are averages.

Panel A: Annual summary statistics

Variables	Units	1995	1996	1997	1998	1999	2000	2001
Purchases	($ '000)	22435.0	27303.8	31473.3	34887.9	43729.4	48585.6	30719.4
Redemptions	($ '000)	16221.6	20232.6	25292.9	31051.4	36956.7	41570.3	28125.5
Reinvestments	($ '000)	4036.5	6245.4	7912.1	5924.0	8756.2	10809.3	1544.8
Change Flows	($ '000)	10274.1	13350.9	14118.3	9811.6	15544.8	17874.5	4159.1
Purchases	Shares	1059.5	1236.3	1290.9	1318.4	1408.9	1407.2	1309.0
Redemptions	Shares	812.5	933.2	1074.6	1290.9	1356.2	1272.2	1245.3
Reinvestments	Shares	180.8	251.9	331.8	226.0	264.7	453.4	69.4
Change Flows	Shares	428.7	557.2	549.5	256.2	318.2	590.1	134.2
Purchases	%	4.06	4.25	4.68	4.71	4.84	5.17	4.71
Redemptions	%	3.04	3.20	3.67	4.33	4.64	4.60	4.12
Reinvestments	%	0.61	0.83	0.89	0.57	0.66	1.09	0.20
Change Flows	%	1.66	1.92	1.94	1.01	0.89	1.68	0.83
TNA	$ millions	708.0	842.0	1013.9	1206.1	1364.6	1537.0	1185.1
Expenses	%	1.277	1.294	1.269	1.262	1.262	1.260	1.256
Month/fund Obs		5521	6622	7227	8259	9151	9961	10691
Fund Observations		507	559	623	712	777	846	923

Panel B: Monthly summary statistics

	1	2	3	4	5	6
Shares purchased	1565.1	1338.4	1486.6	1380.3	1299.3	1152.5
Shares redeemed	1321.1	1232.3	1395.4	1128.5	1066.0	1036.5
Shares reinvested	33.0	19.7	46.3	13.0	46.7	110.1
Shares change in flows	278.4	126.9	138.8	266.0	280.6	227.2
Observations	4619	4649	4657	4702	4722	4753
	7	**8**	**9**	**10**	**11**	**12**
Shares purchased	1268.9	1243.0	1195.9	1242.1	1183.4	1369.8
Shares redeemed	1133.2	1167.8	1142.5	1116.3	1032.3	1342.3
Shares reinvested	23.9	67.8	68.1	71.2	254.9	2215.9
Shares change in flows	161.8	144.1	122.4	198.6	409.1	2246.7
Observations	4834	4862	4875	4898	4914	4947

Table 2 Measuring investor sensitivity

This table provides regression results of shares redeemed each month and divides the sample by various fund characteristics. Each regression includes monthly shares redeemed as the dependent variable where shares redeemed are the dollar redemptions divided by current NAV. SHRNEWY1 is the new shares coming into a fund between month -1 to -12 from the observed redemption. This variable is interacted with three indicator variables identifying is the fund's annual performance from months -1 to -12 was in the top 20% (HIGH), middle 60% (MED) or bottom 20% of funds within their ICDI category at each point in time (LOW). RKPERF is the annual rank performance by ICDI category from months -1 to -12 and this variable is also interacted with the same indicator variables HIGH, MED, and LOW. AVGSHROUT are the average shares outstanding from months -1 to -12. Finally, ID00_02 indicates if the year is either 2000-02. In Panel A, the sample is divided into B shares defined as those shares reporting a positive deferred load but no other front-end or rear load. In Panel B, funds are divided by their annual performance in months -13 to -24 where high performing funds were in the top 20% of funds within its ICDI category in months -13 to -24 and low performing funds were in the bottom 20%. Panel C identifies those funds whose management expenses were in the top 20% of funds and the bottom 20% of funds (excluding index funds from this ranking). Finally, Panel D separates index funds from actively managed funds. To control for the overlapping nature of the data, the coefficients reported are an average of 12 regression coefficients performed separately by month. The t-stats reported are the average coefficient divided by the standard deviation of the twelve coefficients divided by the square root of 12.

Variables	**All**	**Lagged Return**		**Load**		**Index**		**Size**	
		Low	**High**	**No**	**Yes**	**No**	**Yes**	**Small**	**Large**
Shrnewy1*High	0.049	0.053	0.052	0.045	0.051	0.050	0.026	0.079	0.049
	20.27	*9.61*	*22.05*	*9.29*	*16.70*	*19.16*	*5.37*	*5.66*	*19.45*
Shrnewy1*Med	0.067	0.071	0.067	0.038	0.072	0.068	0.017	0.059	0.067
	22.78	*7.95*	*19.62*	*12.82*	*23.47*	*22.46*	*2.47*	*21.58*	*22.66*
Shrnewy1*Lo	0.087	0.084	0.101	0.065	0.096	0.087	0.036	0.077	0.087
	9.04	*7.15*	*11.41*	*7.13*	*9.01*	*9.12*	*4.04*	*11.34*	*8.74*
Avgshrout	0.003	0.006	0.001	0.011	0.001	0.004	0.015	0.015	0.003
	4.45	*2.82*	*0.61*	*13.00*	*1.06*	*4.74*	*5.26*	*7.44*	*4.80*
Rnkret*High	-0.225	-0.187	-0.101	-0.265	-0.417	-0.194	-0.532	-0.086	-0.554
	-2.33	*-1.72*	*-1.08*	*-5.68*	*-3.12*	*-1.94*	*-3.27*	*-3.19*	*-2.78*
Rnkret*Med	-0.761	-0.648	-0.535	-0.246	-1.329	-0.710	-0.575	-0.073	-1.611
	-9.50	*-6.53*	*-4.44*	*-2.54*	*-8.56*	*-9.22*	*-2.08*	*-3.73*	*-10.16*
Rnkret*Lo	-2.313	-0.692	-4.549	-0.982	-5.379	-2.089	-3.651	-0.239	-4.830
	-2.73	*-1.40*	*-4.16*	*-1.55*	*-4.27*	*-2.44*	*-2.16*	*-2.10*	*-2.68*
Intercept	0.367	0.277	0.261	0.262	0.646	0.338	0.668	0.020	0.792
	6.34	*4.50*	*3.10*	*4.89*	*10.74*	*5.82*	*4.43*	*2.19*	*6.55*

Table 3. Regime Shifting Model

This table provides estimates from our regime shifting model which estimates fund redemptions as a weighting between sensitive and insensitive investors.

$$f(R_{it+1}) = P_{it}^{sens} f(\varepsilon_{it+1}^{sens}, \alpha_{sens}) + (1 - P_{it}^{insens}) f(\varepsilon_{it+1}^{insens}, \alpha_{insens})$$

where the probability is logistic

$$P_{it}^{sens} = \frac{\exp(\theta W_{it})}{1 + \exp(\theta W_{it})}$$

The probability of a sensitive investor is defined by several variables. The LAGGED RETURN measures the ranked annual return between months -13 to -24 from the time that redemptions are measured. TNA is the size of the fund. INDEX identifies 1 if the fund is an index and zero otherwise. LOAD identifies 1 if the fund charged loads on inflows and zero otherwise. In the sensitive redemption equation, SHRNEWY1 is the aggregate new shares flowing into a fund between months -1 to -12. This variable is interacted with three indicator variables identifying is the fund's annual performance from months -1 to -12 was in the top 20% (HIGH), middle 60% (MED) or bottom 20% (LOW) of funds within their ICDI category at each point in time. RNKRET is the annual rank performance by ICDI category from months -1 to -12 and this variable is also interacted with the same indicator variables HIGH, MED, and LOW. AVGSHROUT are the average shares outstanding from months -1 to -12. The same variables are used in the equation identifying insensitive investor with the exception that SHRNEWY1 and RKRET is not interacted with the HIGH, MEDIUM, and LOW indicator variables as means to identify the sensitive investors. This uses all data from 1995-2002.

		Coef	t-stat
Prob of Sensitive	**Intercept**	-2.5880	-89.4
	Lagged Return	1.2734	505.5
	TNA	0.0521	19.0
	Index	-0.0119	-0.5
	Load	-0.3713	-10.3
Sensitive Redemptions	**Intercept**	0.3705	159.2
	Shrnewy1*High	0.0644	31581.4
	Shrnewy1*Med	0.0601	721.7
	Shrnewy1*Low	0.1096	457.1
	Avgshrout	0.0170	25255.6
	Rnkret*High	-0.2463	-30.0
	Rnkret*Med	0.1795	23.3
	Rnkret*Low	-0.8463	-45.3
Insensitive Redemptions	**Intercept**	0.2250	39.1
	Shrnewy1	0.0340	191.4
	Avgshrout	0.0100	161.9
	Rnkret	-0.2356	-52.2
	Variance	0.9175	526519.5
Tests	**Shrnewy1*High = Shrnewy1**	0.030	9.51E+05
	Shrnewy1*Med = Shrnewy1	0.026	137.49
	Shrnewy1*Low = Shrnewy1	0.076	234.75

Table 4. Expected fees using estimates of the regime model

From our regime model in Table 3, we can estimate the expected ATTRITION RATES and expected fees for a fund. To calculate the attrition rates, we calculate the probability weighted coefficients on SHRNEWY1. If a fund was performing in the top 20% of funds currently the coefficient on SHRNEWY1HI would be used as the weighted by P_{it} for sensitive investors and the coefficient of SHRNEWY1 for the insensitive investors would be weighted by $1\text{-}P_{it}$ where

$$P_{it}^{sens} = \frac{\exp(\theta W_{it})}{1+\exp(\theta W_{it})}$$

and θW_{it} is defined by four variables, LAGGED RETURN, TNA, INDEX, and LOAD. The LAGGED RETURN measures the ranked annual return between months -13 to -24 from the time that redemptions are measured. TNA is the size of the fund. INDEX identifies 1 if the fund is an index and zero otherwise. LOAD identifies 1 if the fund charged loads on inflows and zero otherwise. The HALFLIFE is calculated as LOG(0.5)/(LOG(1-ATTRITION RATE) x 12). The expected fees assume that the manager charges a 1% annual fee and are calculated as 0.01/12 x (-1/LOG(1-ATTRITION RATE)) x 100. The fees earned per dollar of inflows are simply the expected fees (above) multiplied by SHRNEWY1 for each fund.

Panel A:				
	Mean	**Min**	**Max**	**St Dev**
Estimated Attrition	0.0389	0.0268	0.0937	0.0035
Halflife (Years)	1.4679	0.5873	2.1271	0.1166
Expected Fees (Base 1%)	0.02118	0.0085	0.0307	0.0017
Load fund expected fees	0.02125	0.0085	0.0232	0.0016
No load fund expected fees	0.02112	0.0095	0.0307	0.0018
Inflows * Fees	0.4468	0.0000	35.6259	1.3670

Panel B: Expected fees (Base 1%) by performance				
	Current Rank Returns			
		Low	**High**	**All**
Lagged Rank	**Low**	0.0206	0.0225	0.0220
Returns	**High**	0.0168	0.0205	0.0200
	All	0.0190	0.0214	