Mutual Fund Risk and Market Share Adjusted Fund Flows

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Abstract

A long literature has examined the relationship between performance and subsequent fund flows. Prior work takes fund dollar flows divided by their assets under management as the dependent variable. The null hypothesis implied by this choice is that fractional fund flows are a constant: independent of performance. However, individual fund flows have to add up to the aggregate flow in every period. If aggregate flows are high then on average so must individual flows, and vice-versa. To accommodate this accounting identity, this paper proposes using market share as the dependent variable. Unlike percentage flows, market shares always add to the aggregate value: one. With market shares as the focus, the conclusion drawn here is that adding volatility to a fund's return process does not increase a firm's funds under management. Thus, contrary to the prior literature this paper does not support the idea that fund flows provide managers with an incentive to engage in additional risk taking.

Numerous papers have documented a convex relationship between mutual fund flows and past returns, including Chevalier and Ellison (1997), Sirri and Tufano (1998), Fant and O'Neal (2000), Huang, Wei, and Yan (2007). Convexity appears to hold under a wide variety of definitions for either flows or past performance ranking criteria. The strength and robustness of this relationship has in turn generated another literature that examines its implications for fund management including Brown, Harlow, and Starks (1996), Taylor (2003), Dasgupta and Prat (2006), and Kempf and Ruenzi (2008). At the same time there is strong evidence that finding funds with forecastable abnormal performance is difficult at best, and likely impossible with the tools most consumers have readily available.[1] Conversely, it is a simple matter for a fund to boost its short term risk (however measured) in order to increase the chance that its subsequent returns will let it "stand out" from the pack. All of this has induced researchers to hypothesize that funds take on risk as a way to increase their expected fund flows. This paper examines the degree to which this result may be due to the null hypothesis implied by the regressions that have been run as opposed to consumer behavior.

Imagine the goal was to estimate the impact of an advertising slogan on a casual dining firm's sales rather than performance on fund flows. In the former case, the null hypothesis would be that the advertising campaign did not impact sales. But, how would you measure it? The natural null hypothesis is that the advertising did nothing, leaving the firm's *market share* unchanged. Not sales but market share. Sales make a poor

[1] Papers that have discovered way to forecast excess mutual fund returns have typically used methods unavailable to most individual investors. Examples include, Chen et al. (2000), Bollen and Busse (2004), Cohen et al. (2005), Avramov and Wermers (2005), Busse and Irvine (2005), Kosowski et al. (2007), Kacperczyk, et al. (2008), and Cremers and Petajisto (2009).

dependent variable since they go up or down whenever macroeconomic effects cause the industry's sales to go up or down. In contrast, market share automatically controls for this. The marketing analogy is relevant to the fund flow-performance literature because the hypothesis is that performance draws in customers just as an advertising campaign does.

Despite the similarity between the fund flow-performance problem and that of measuring the impact of a marketing campaign, finance papers do not use a fund's market share as the dependent variable. Rather the typical specification uses a fund's percentage flow. That is its dollar flow divided by its assets under management (AUM). This is not a specification without consequences since it lets the aggregate flows violate what one might term an "adding up constraint." If an investor sends a dollar to one fund he has necessarily not sent it to another. In aggregate this simply means that individual fund flows must add up to the aggregate flows for the period in question. Market share changes reflect the impact of this choice automatically. Percentage dollar flows do not.

This paper reexamines the fund flow-return relationship by looking at it through the lens of market shares. By doing so the empirical model alters the underlying null hypothesis. In the current literature the implicit null is a fund's flows are independent of its returns. Here the null is that a fund's market share is independent of its performance. The basic idea is that under the null if a fund has 1% of the market then it should expect to receive 1% of any aggregate flows all else equal. Relative returns are then allowed to influence its flows but only by shifting the fund's flows from this baseline and thus at the cost to some other fund. Including this one constraint has a dramatic impact on the estimates. Instead of finding a convex relationship between flows and returns (or ranks) the results point to one that is closer to linear. More importantly, however, the estimates indicate that mutual funds do not have an incentive to increase their risk to draw in flows.

This paper questions whether or not fund flows encourage managers to increase their portfolio risk not whether they vary their fund's risk over time. Thus, the analysis conducted here should not be taken as a critique of articles or parts thereof on the latter topic like those by Brown, Harlow and Starks (1996), Chevalier and Ellison (1997), Taylor (2003), Busse (2001), Qiu (2003), and Goriaev, Jijman, and Werker (2005). It may be the mutual fund managers do vary their fund risk in response to tournament like incentives. What this paper indicates, however, is that the driving force behind those incentives may not be consumer fund flows. For example, Qiu (2003) attributes the time varying fund volatility in his dataset to termination risk. Undoubtedly, other career issues like bonus payments and the like may induce similar incentives.

The paper is organized as follows: Section 1 looks at some long term patterns that seem difficult to reconcile with a convex flow-performance relationship. Section 2 discusses the mathematical implications from various empirical specifications of the fund return-flow relationship. Section 3 looks at how requiring individual fund flows to add up to the aggregate impact the empirical modeling of the problem. Section 4 discusses the data used. Section 5 presents summary statistics. Section 6 looks at aggregate flows and tests one of the embedded implications within empirical models that regress fractional fund flows on performance. Section 7 presents the paper's initial findings regarding how market shares react to past performance. Section 8 discusses bootstrap simulations linking performance and a fund's market share growth. Finally, Section 9 presents the paper's conclusions.

1 Some Long Term Patterns

If the flow-performance relationship is indeed convex Jensen's inequality implies that volatile funds should grow relative to their peers. However, the long term trends displayed Table 1 do not indicate that this has been happening. Each column displays the aggregated year end market shares of funds grouped according to various measures of risk.[2] The second column shows that index fund's ended 1991 with 4.3% of the market. By 1996 they had garnered 17.5%. Arguably, these are the funds with the least risk. Yet their market share growth has been substantial. One might suspect that index funds have grown despite their low risk because they offer lower expenses and thus somewhat higher returns. Under this hypothesis the reduced growth from low risk is offset from higher growth from a larger average return. But the table offers no evidence that actively managed high volatility funds have seen their market share grow. The columns displaying the market shares of funds with very low and low active shares show some combined growth until about 1998 and have since leveled off with about 10% of the market. Over this same time period high active share funds, which are presumably among the most volatile, have seen essentially no growth.

The final four columns in the Table 1 track the market shares of fund classified by tracking error. As with the other measures there is no evidence that highly volatile funds have seen any long term market share growth. The columns TE D1 and TE D10 display the market shares of funds in the lowest and highest tracking error deciles respectively. While each category has seen some variation in market shares over time, there is no apparent long term trend one way or the other. Also, note that the lowest tracking error

[2] See Cremers and Petajisto (2009) for definitions and www.sfsrfs.org for the underlying data.

decile has historically had a market share of around 20% while the highest is much smaller with only about 4.5% or so. The final two columns list the tracking error cutoffs for the two deciles over time. To get into decile 1 in a particular year a fund needs a tracking error below the value in TECO D1. Similarly, a fund is included in decile 10 if its tracking error lies above TECO D10. Again there appears to be little long term trend towards volatile funds. The cutoffs have not shown a consistent increase or decrease over time. If volatile funds were growing relative to their peers one would have expected the low and high decile group's cutoffs to increase over time as the average fund's tracking error increased. This does not appear to be happening. If fund flow are convex in returns, it is not apparently showing up in the long run relative market shares.

2 Ranks and Convexity Econometrics and Implications

The idea that fund flows are globally convex in past returns along with Jensen's inequality is not inconsequential. If it is true, then as individual fund returns vary cross sectionally the expected value of flows in the aggregate will positively vary with them. Consider a two fund example. Assume that if they have identical returns they split the aggregate flow and that the aggregate flow is independent of their relative return. For ease of discussion, but without consequence, assume the aggregate flow is zero. In this case one fund cannot attract new funds without the other losing an identical amount.

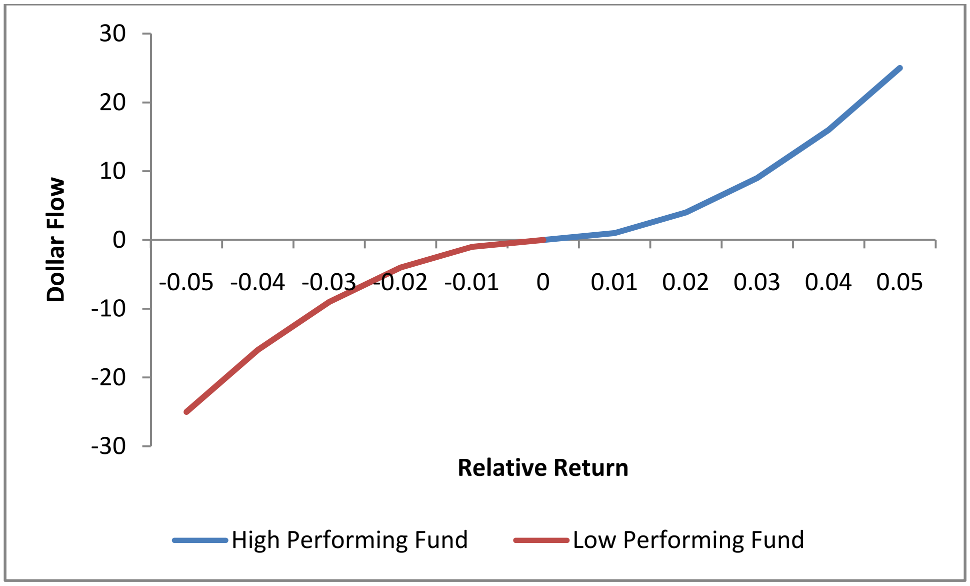

Figure 1

Global convexity simply cannot hold here as that would imply that their aggregate flows increase as their past returns diverge.[3] It is possible that the relationship between each fund's relative performance and fund flows is, for example, concave and then convex from high to low but it cannot be globally convex. In fact, with just two funds the return-flow relationship has to be symmetric around zero. That is, if the better performing fund faces a convex function the underperforming one must face a symmetric concave one.[4]

From Jensen's inequality, if fund flows are convex in relative fund returns then increasing the spread among returns must result in a larger aggregate fund flow.[5] Intuitively this may seem odd. Why should investors increase their aggregate investments in mutual funds when fund returns are particularly spread out? The solution

[3] In the figure if the aggregate flows were non-zero the y-axis is simply centered at a value equal to half the aggregate flow. For example, if aggregate flows were 20 then each fund would receive half of that amount if they had identical returns and thus the y-axis would be centered at 10.

[4] This example is presented primarily to help develop the paper's intuition. But, those that have seen it seem to have turned it into a challenge: can universal convexity hold with three or more funds? The appendix offers up a formal discussion of this issue and shows that the intuition holds no matter how many funds there are.

[5] See the Appendix for a proof of this statement.

has been to finesse this issue by converting fund returns into ranks that are normalized to lie within some interval, which for ease of discussion take to be -1 and +1.[6] With two funds the ranks equal -.5 and +.5 no matter what the gap between their past returns.[7] This, of course, allows for a globally convex function from past returns to fund flows without tying aggregate flows to the spread in past returns. All one requires is that switching any set of ranks does not alter the set of dollar flows.

While in principle one can use ranks to separate relative returns from aggregate flows, the empirical specification typically used does not. Most rank based models assume the fund flow–return rank relationship for firm *i* on date *t* is governed by:

$$\frac{f_{i,t}}{n_{i,t-1}} = a_0 + g\left(k_{i,t-1}\right), \tag{1}$$

where *f* is the dollar flow in the period, *n* the funds total AUM, *g* a function that maps the firm's rank *k* into its flow, and a_0 a constant. Notice that equation (1) maps ranks to percentage flows relative to the fund's total AUM. However, if this relationship is to hold and if $\partial g / \partial k_{i,t-1} > 0$ then aggregate flows must be related to how large funds do relative to small ones. For example, take two funds labeled 1 and 2. Now consider the total flows going to these two funds. Next suppose they switch ranks. Using (1) the sum of their dollar flows ($f_{1,t}$+$f_{2,t}$) will only be invariant to this swap in rankings if the two

[6] The use of ranks in empirical studies of consumer cash flow allocation across mutual funds appears to go back to the working paper that formed the foundation of Sirri and Tufano (1998). The earlier article by Ippolito (1992) and the contemporaneous paper by Chevalier and Ellison (1997) used returns in excess of the market. Since then, however, the use of ranks seems to have become widespread if only in some cases to split data into two halves with low and high performers. See for example Brown, Harlow and Starks (1996), Busse (2001), Elton, Gruber and Blake (2003), Lynch and Musto (2003), Huang, Wei, and Yan (2007), and Kempf and Ruenzi (2007). Recently, Ivković and Weisbenner (2009) have looked at how both ranks and returns impact individuals fund allocation decisions.
[7] With a zero in the unlikely event both funds tie. But, since this is an empirically irrelevant case it will be ignored here.

funds are of identical size ($n_{1,t-1} = n_{2,t-1}$). Otherwise, if the large fund moves up in rank then the total flows will increase, and if the large fund moves down they will decrease.

Based on the above analysis, if equation (1) holds then one has the following testable empirical implication:

Proposition 1: *If equation (1) holds then aggregate fund flows will increase as the ranks of the industry's larger funds increase.*[8]

There are numerous ways one can test to see if Proposition 1 holds. Ultimately, what is needed is a measure relating aggregate flows to the size of the funds with the highest ranks. The empirical section of this paper employs two such measures: The first uses

$$\frac{F_t}{N_{t-1}} = a_0 + \frac{a_1}{N_{t-1} I} \sum_{i=1}^{I} n_{i,t-1} k_{i,t-1} + controls, \tag{2}$$

where F_t is the aggregate industry flow in period t, and N_t the industry's Total Assets Under Management (TAUM) ; $\sum_i f_{i,t}$ and $\sum_i n_{i,t}$ respectively. Since the summation in (2) increases with the ranks of the larger funds it should yield a positive value for a_1 under Proposition 1. The second test conducted here simply replaces the summation in (2) with the covariance between fund size and fund rank.

$$\frac{F_t}{N_{t-1}} = a_0 + \frac{a_1 I}{N_{t-1}} \operatorname{cov}\left(k_{i,t-1}, n_{i,t-1}\right) + controls. \tag{3}$$

Again, under this measure a_1 should be positive if Proposition 1 is true.[9]

[8] One can in theory break this dependence on aggregate flows and the performance of funds by size by dividing $g(k_{i,t-1})$ by $n_{i,t-1}$. However, this independence relies on what is essentially a knife edge specification. Any other variation in the relationship between g and n will destroy the independence of F on the ranks. Nevertheless, the authors checked to see if the knife edge case holds in the data. This was done by conducting statistical tests in which additional terms involving g and n were included in the estimation of (1). Not only were many of these additional terms statistically significant the parameter estimate for g/n was not. Interested readers can obtain a copy of the exact set of models that were estimated along with the results from the authors.

3 Adding Up Constraints, Fund Flows and Incentives

Whether or not relative returns between small and large funds impacts aggregate flows, the sum of the market shares both before and after the flows arrive must equal one.[10] Thus, one approach is to begin with a statistical specification that is guaranteed to have this property as both its null and alternative hypothesis. Within the framework of market shares, the natural statistical null hypothesis is that a fund's expected market share remains unchanged period to period.[11] To capture this idea let $u_{i,t}$ represent fund *i*'s unexpected change in market share in period *t*. Then $u_{i,t}$ can be written as:

$$u_{i,t} = \frac{n_{i,t}}{N_t} - \frac{n_{i,t-1}}{N_{t-1}}. \tag{4}$$

The left hand side of equation (4) captures the change in a fund's market share due to both the flows it receives and the returns generated to garner them. The literature has traditionally tried to isolate dollar flows from fund returns. In part this was dictated by the use of (1) in which flows were divided by a fund's initial AUM. But, fund managers care about the total funds they have under management. For risk to pay off for them it must be that the total gains in a fund's AUM in high return periods more than offset the losses in low return periods. If not, then additional risk will not generate an increase in future expected fees.

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[9] While both Werther (1995) and Fant (1999) examine aggregate flows neither examines how they vary in response to the rank performance of funds of various sizes. Werther does, however, look at what might viewed the inverse question: the impact of fund flows on stock returns across stock size deciles.

[10] Industry can always be defined as the set of funds currently being ranked against each other. Thus, market share is relative to the market for which data is being drawn. Similar to comparing luxury car market shares rather than overall automobile market shares.

[11] Of course, this does not rule out alternative hypotheses. For example, one might suspect that market share changes are serially correlated. This might occur if a particular fund goes from being excluded to included in a large 401(k) plan. Naturally, the equation can be adapted to this and any number of other scenarios.

Even though the error term in (4) has a number of desirable properties, it is not likely to be homoskedastic across funds. Larger funds will naturally see a greater variation in their market share changes. One might consider mitigating this by dividing the right hand side of (4) by the fund's initial market share. However, doing so destroys the adding up condition that the errors ($u_{i,t}$) sum to zero under all circumstances. This is not trivial since it will likely imply that the sum of the market share changes will depend upon whether larger or smaller firms do particularly well, which is clearly impossible. Another route, and the one used here, is to instead examine the results both on a fund-by-fund basis and in funds-of-funds that have equal initial market shares.[12] Because the synthetic funds in the fund-of-funds approach have equal initial market shares this should eliminate any effects due to size related heteroskedasticity.[13] In any case, the fund-by-fund and fund-of-funds tests can always be viewed as robustness checks for each other.

While (4) provides a useful place to start, most studies are interested in whether or not a fund's volatility impacts its value. (People naturally expect there to exist a positive relationship between a fund's size and its performance so that is not much of an issue.) A typically study therefore uses as its null hypothesis that flows as a percentage of a fund's AUM depends linearly on the fund's return rank. The alternative is that it is not. Here this hypothesis is reformulated in terms of market shares. In this case the null hypothesis is that market share changes are independent of a fund's return rank. What might then be called the base alternative hypothesis is that the change in market share is linearly related to fund flows. The primary alternative then is that it is not, in which case there may be

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[12] An analog to this procedure can be found in studies that compare results when firms are equally weighted and value weighted. The former corresponds to this paper's tests on a firm-by-firm basis and the latter to tests using equal market share groupings.

[13] Of course, heteroskedasticity does not lead to biased coefficients. At worst it should reduce the efficiency with which parameters are estimated.

some incentive for managers to alter their risk profile in the hope of growing faster than their competitors.

Based on the above discussion, the goal is to create an empirical specification in which the base null, as well as the base and primary alternative hypotheses can all be tested against each other. The following specification meets these three goals:

$$\frac{n_{i,t}}{N_t} - \frac{n_{i,t-1}}{N_{t-1}} = a_0 + g\left(k_{i,t}\right) + controls_{i,t} + u_{i,t}. \tag{5}$$

As a practical matter g is assumed to follow a step function of some sort. Thus, funds are placed in one of a smaller number of groups (say deciles) based on their returns and g is then estimated via a set of dummy variables. In this case (5) becomes,

$$\frac{n_{i,t}}{N_t} - \frac{n_{i,t-1}}{N_{t-1}} = \sum_{j=1}^{D} a_j d\left(k_{i,t-1}\right) + controls_{i,t} + u_{i,t}, \tag{6}$$

where a_j is an estimated dummy parameter, and d a mapping from ranks into zero-one dummies for each of the D-cile groups. This leads to the following proposition which spells out the empirical questions that are typically of interest.

Proposition 2: *Under the alternative that fund flows are convex in ranks the difference between a_j and a_{j-1} should be increasing in j.*

While Proposition 2 lays out the alternative hypothesis that has often been the primary focus within the literature. Economically, however the question of interest is really whether or not fund flows react to returns in a way that encourages managers to increase the risk of their portfolio. This leads to the next proposition that will ultimately form this paper's focus.

Proposition 3: *Given the parameter estimates in* (6)*, increasing a fund's return volatility will yield a positive expected change in market share. Equivalently* $E\left[n_{i,t}/N_t - n_{i,t-1}/N_{t-1}\right]$ *is increasing in a fund's return volatility.*

4 Data

The data comes from the CRSP survivorship bias free mutual fund data set and the addenda page for Cremers and Petajisto (2009) at www.sfsrfs.org. From the CRSP data only non-specialty domestic equity funds are included in the final sample (Lipper Objectives EI, EIEI, ELCC, EMN, G, GI, I, LCCE, LCGE, LCVE, LSE, MC, MCCE, MCGE, CMVE, MLCE, MLGE, MLVE, MR, SCCE, SCGE, SCVE, and SG). The analysis that follows uses category adjusted returns. These are created by taking a fund's return and subtracting the average return for funds that have the same Lipper Objective code in that period.

To be included in a particular period a fund's data has to include its AUM, and returns. This data contains quarterly Assets Under Management (AUM) since 1970 and monthly AUMs since 1991. Funds are also dropped from periods in which their flows appear to be due to data entry errors. If flows in periods t and t+1 have opposite signs and are both at least ten times larger than then flows in both periods $t-1$ and t+2 then that fund is removed from that period's data.

5 Summary Statistics

Table 2 Panel A presents summary statistics for traditional flow measures $f_{i,t}$ and $f_{i,t}/n_{i,t-1}$. While statistics were calculated for each year, in the interest of space the table only presents data from every 5 years for the quarterly data and every other year for the monthly data. The important item to note is that aggregate fund flows relative to AUM have been fairly volatile over time. The average across funds has ranged from a low of −4.8% in 1976 to a high of 17.8% in 1996. In general however, over the sample period they have been positive. From this it seems desirable that any statistical equation that attempts to measure how individual fund flows react to returns should probably account for both the large time variation in aggregate flows and that they have been positive in most years over the sample period. Market share changes automatically handles both issues; they add to zero no matter what the aggregate flow may be. As a result, time variation in the aggregate fund flows cannot induce misspecification error of some sort.

The latter columns of Table 2 Panel A display the time series distribution of market shares in the sample. Over time it appears the mutual fund industry has become less and less concentrated. However, one trait that has remained constant is that fund sizes are very right skewed. Funds in the 90^{th} percentile are far larger than the median fund.

Panel B in Table 2 tabulates the distribution of the two measures proposed correlating fund sizes and returns to test whether or not aggregate fund flows are positively correlated with how well larger funds do. Based on these statistics it appears that contrary to what one might otherwise suspect, given the size of the mutual fund industry, there appears to be a great deal of variation in how well large funds do relative to small ones over time.

6 Aggregate Flows

Aggregate flows are measured using the procedure found in Warther (1995). First, the raw aggregate flow measure is constructed as dollar flows into and out of existing mutual funds. Next this value is divided by the total value of the U.S. stock market at the prior month's end as reported by CRSP. The purpose of this procedure is to correct for changes in the value of the investment pool over time. Thus, one now has the fraction of the market's total value moving into and out of mutual funds each period.

Recall that if fund flows are convex in return ranks, then as shown in Proposition 1 this implies aggregate flows should be positively correlated with how well the larger funds perform. Table 3 presents several tests of this hypothesis using the measures proposed in equations (2) and (3). To construct the table funds are grouped into vigintiles (20 bins each with 5% of the data). Each group's lagged AUM and rank are interacted based on the measure and then used as independent variables to explain aggregate flows.

Overall, the results in Table 3 offer little support for the idea that aggregate fund flows are impacted to a statistically significant degree by the performance of the largest funds in the industry. Using quarterly data only four of the 16 relevant *t*-statistics are even significant at 10% level. With monthly data none are. Beyond that many of the test parameters are negative implying a negative (although again at best marginally statistically insignificant) relationship between how well the larger funds do and the aggregate flows. These results do not appear to arise from a lack of power. The statistical model has little trouble detecting the impact of past market returns on aggregate fund flows. Also, from Table 2 Panel B the variable Sum(TAUM×Rank) has a relatively wide distribution as does the covariance between TAUM and Rank which should let the model detect their impact, if any, on aggregate flows.

The evidence in Table 3 is inconsistent with the idea that investors are reacting to the relative distribution of performance and size when determining how much to invest in the mutual fund industry. As shown in Proposition 1 this is contrary to what the typically estimated performance-flow model derived from equation (1) implies. The parameter estimates are not, however, inconsistent with the alternative model of market share competition proposed in equation (5) and explored in the following sections.

7 Changes in Market Shares as the Dependent Variable

As pointed out earlier market shares are naturally independent of the aggregate flows. Furthermore looking at the problem via market shares gives some new insights into the problem facing a typical mutual fund manager. Unless adding risk to the fund's return results in a net expected increase in market share managers have no incentive to ramp up their portfolio's risk in the hope of generating additional growth and thus fees.[14]

Most of the analysis in this section is done by looking at funds grouped into vigintiles. As noted earlier, market share changes are likely to be larger when a fund is larger. By grouping funds into vigintiles this effect is somewhat mitigated since each bin contains 5% of the TAUM. In essence, each vigintile is itself a mutual fund-of-funds.

Table 4 begins this section's analysis with a comparison of the relationship between percentage flows and changes in market share by return rank. Figure 2 displays the results in graphical form. Each year funds are grouped into vigintiles that include 5% of all assets under management based upon their past performance as measured by their raw or category adjusted returns. After the performance ranks are estimated, the average change in market share or percentage flow is then calculated. The resulting value is then averaged over periods to generate the value displayed in the table.

[14] Again, they may have other reasons to manipulate their fund's risk that are independent of expected market share growth.

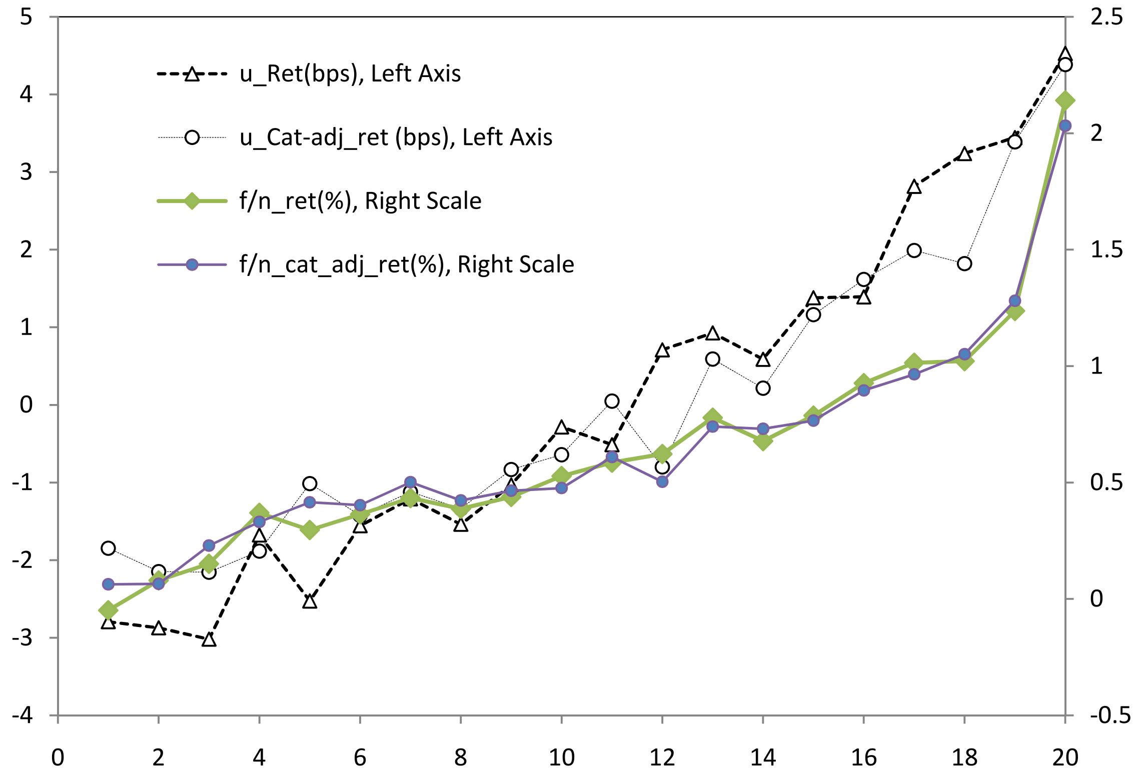

Figure 2

Looking at the graph, the relationship between a fund's fractional flow and a firm's rank exhibits the well known convex shape found as far back as Sirri and Tufano (1998). The relationship, however, appears to be closer to linear when market share changes are considered. Thus, while the fractional flow measure seems to indicate a clear incentive for funds to increase their risk to attract assets, the evidence for this tactic's value is considerably less obvious when market share changes are used.

Table 5 repeats the analysis in Table 4 but now in a piecewise regression framework. To test for convexity the linear function is allowed to have two kinks. The location of each kink is estimated by finding the points that maximize the average R^2 across periods in each specification. Panel B reports the vigintile where the kink is estimated to occur. Using the traditional flow measure ($f_{i,t}/n_{i,t-1}$) the slope of the line increases at each break point and is statistically significant. In contrast, when changes in market share are used the slope parameters are not uniformly increasing in value. Of the four estimated slope coefficients for the upper two lines only one is statistically significant and then only at the 10% level. Thus, at best, one might conclude that there is very weak evidence that market share changes are convex in returns.

Not only do the results in Table 5 offer at best weak statistical support for a convex relationship between market share changes and returns the economic significance seems weak as well. A move from one rank vigintile to the next increases the dependent variable by 0.05 (since ranks are normalized to lie between zero and one). Now consider the slope estimate offering the most support for convexity: that for the highest category adjusted return group. This parameter has an estimated slope coefficient of 0.2156. Therefore, the total impact on a *vigintile's* percentage change in market share is 0.05×0.2156=0.01078 or 1.078bps since the dependent variable is already in percentage terms. In contrast a vigintile's market share is, by construction, 500bps. So if the funds in a vigintile where to move up one return rank their market share would increase by only about 1.078bps. Any impact convexity might have would thus have to be much smaller since one should subtract the expected loss from the increased spread in the low end of the distribution. Add to this the finding by Huang, Sialm, and Zhang (2009) that funds which vary their risk exhibit inferior future performance and the economic incentive to game fund flows via increased risk can only be further diminished.

While the estimates in Table 5 suggest that managers may have at most a small economic interest in increasing their fund's risk it is far from definitive. The piecewise linear regression can only pick up the most basic patterns. But, given how small the magnitudes appear to be even small nonlinearities within the ranks may not lead high risk funds to gain market share. To check for this and other possibilities the next section of the paper takes a more direct look at managerial incentives with regard to altering a fund's risk to attract flows.

8 Managerial Incentives

8.1 Regression Analysis

This section uses a standard Fama-MacBeth style regression to examine the degree to which market share changes may be convex in returns. Table 6 displays the results. Models 1 through 3 regress subsequent market share changes on a fund's return rank (*Rank*). Models 4 through 6 repeat the analysis using a fund's actual return (*perf*). Panel A measures returns using a fund's raw return minus the market return. Panel B conducts the same analysis but this time uses a fund's return minus the return for the average fund in its Lipper category. If market shares are convex in performance then this should be picked up by either the $Rank^2$ or $perf^2$ parameter estimates.

The control variables used in the Fama-MacBeth style regressions are as follows: *Cat_flow* is the monthly dollar flow divided by the one month lagged AUM for all funds in the category, *Fee* is the fund's annual expense ratio plus actual 12b-1 fee in the prior calendar year, *LogAge* is the log of the fund's age since inception in years, *LogSize* is the log of the fund's AUM in millions, *vol* is the standard deviation of fund's return over the prior calendar year, *Turnover* is the fund's turnover ratio from the prior calendar year, and *Lag_u* is the prior period's change in market share.

The evidence for convexity in Table 6 Panel A is very weak. While three out of four estimates using either $Rank^2$ or $perf^2$ are positive none are statistically significant. In comparison the linear *Rank* and *perf* parameters are both positive in the six specifications in which they appear. They are also significant at the 10% level in two and at the 5% level in two others. Panel B offers even less evidence of convexity. In this case three of the four estimated parameters for the quadratic terms are negative. Again, none are statistically significant. Furthermore, this time not only are all the parameter estimates on the linear rank and performance terms positive but five out of six are significant at the 1% level. The contrasting results both in terms of consistency and statistical significance between the linear and quadratic terms indicates that power is not the issue. If it were then one would have expected the linear terms to come out with inconsistent signs and insignificant as well; yet they do not.

As a further check on the statistical power of the regressions the analysis is repeated but this time with the traditional percentage flow measure $f_{i,t}/n_{i,t-1}$ as the dependent variable. The results in Table 7 with respect to convexity differ considerably from those in Table 6. In line with prior studies, the convexity parameter is positive in six out of the eight models in which it appears. In the six runs where it is positive it is statistically significant at the 5% level in four cases, and at the 1% level in two others. The linear term is again positive in all twelve runs and significant at the 1% level in nine of those. Overall, then there appears to be enough data to detect convexity when it exists. The fact that there is minimal evidence for it in Table 6 would thus seem to imply that if a fund's change in market share is convex in performance these tests, at least, cannot detect it.

8.2 Six Month Performance Periods

It is, of course, possible that using a one month return window for the rank formation followed by a one month window for inflows is simply too short a period of time when it comes to mutual funds.[15] Consumers are known to respond slowly. Thus, it may be that using longer windows will show that increasing a mutual fund's risk exposure increases its expected market share. This experiment is carried out in Table 8 and Table 9 where six month performance and evaluation periods are used.

Table 8 and Table 9 basically repeat the prior analysis using market share changes and fractional flows respectively. The results are similar. In Table 8 with market share growth as the dependent variable there is little evidence of convexity. In the eight specifications where the squared convexity term appears (either $Rank^2$ or $perf^2$) it is insignificant in 7 and only significant at the 10% level in the eighth. Again, however, the model has no difficulty picking up a linear relationship between market share growth and returns. In the 12 specifications in which the linear term appears it is significant at the 1% level in eleven of them, and at the 10% level in the twelfth.

Now compare the results in Table 9 with those in Table 8. In Table 9 the dependent variable is the traditional fractional fund flow measure. Using market adjusted returns the convexity parameter is significant at the 10% level in two of the four specifications it appears in. When returns are instead adjusted by category the convexity measure is significant at the 5% level in two specifications and at the 10% in a third. Again, the model is able to detect convexity using the standard fractional flow measure although less than with the monthly data. But whether one uses monthly or bi-annual data the

[15] Along this line of query Goriaeva, Nijmanb, and Werker (2007) find that consumer reaction to performance can lag the actual returns by several months. Thus, one might reasonably suppose that long return histories followed by long flow periods are needed to detect the profits to mutual funds that risk increases might bring.

conclusion is basically the same. The statistical model finds little evidence that increasing a fund's risk will increase its market share growth.

8.3 Does Early Year Performance Impact the Value of Late Year Risk?

Many papers have indicated that funds increase their risk in the latter part of the year. The hypothesis has been that a poor early year performance gives a fund manager a stronger incentive to increase risk in the latter half of the year to take advantage of the convex fund rank-flow relationship. Thus, funds are assumed to do this to increase their expected flow in the following year. But, does this strategy increase a fund's expected market share growth in the following 12 months? Table 10 looks at this issue.

To create Table 10 Panel A the data is sorted into a 10 by 10 panel. Funds are categorized by their return decile in the period January through June in a particular year. Then they are also categorized by their return volatility during July through December of the same year. This creates a 10 by 10 set of independent sorts. Next, for each cell the change in market share of the funds populating it is calculated over the following 12 months. For ease of exposition the three periods are referred to as C_0 (=6), C_1 (=6) and C_2(=12) respectively. Next the changes in market shares are regressed on the various independent variables of interest and a number of controls. In Panel B the analysis is repeated but this time the C_1 sorts are based on the change in volatility (*ds*). The variable *ds* is defined as the fund's return standard deviation from July through December minus the return standard deviation from January through June of the same year. The goal here is to see if increasing a fund's volatility helps, as opposed to just taking on a lot of volatility which is what Panel A examines.

Table 10 Panel A the parameter estimate of interest is for the $Std(C_1)$*perf variable. If poor early year performance implies that a high latter year standard deviation will induce market share growth then this parameter should be negative. In the two specifications it appears in it is insignificant in both cases and has the wrong sign in one. Indeed, regardless of a fund's early year performance taking on risk in the latter part of the year does not seem to help add to a fund's expected market share. The parameter on $Std(C_1)$ is statistically insignificant in every model, and negative in two of the models that use category adjusted returns. Now compare these results to those regarding early year performance – the $Perf(C_0)$ parameter. In this case the statistical model has no difficulty detecting a strong positive relationship. The estimated parameter is positive and significant in all six specifications in which it appears. Perhaps not too surprisingly, if a fund has very good returns from January through June of one year it can expect to see continued market share growth in the following January through December period.

It is possible that if a fund does poorly early in the year the incentive is to add risk to the portfolio rather than just seek out a high level. Under this hypothesis one should find that an increase in risk following poor performance helps to add to a fund's market share. Table 10 Panel B presents the results. This time both of the interaction parameters of interest have the negative sign expected under the fund tournament hypothesis that flows are convex in returns. However, in one case it is not significant at the customary levels and in the other only at the 10% level. Thus, at best the table provides only very weak evidence that adding risk to a portfolio with poor early year performance will help increase a fund's expected market share growth. In comparison, once again, the model has no difficulty finding that good early year performance pays off in increased expected market share growth the following year.

9 Conclusions

There now exists a long literature indicating that fund flows are convex in past performance. This linkage has been established within an empirical model that regresses individual fund flows divided by AUM on past performance ranks and controls. However, this specification is not without its own economic and empirical implications. The null hypothesis is thus that fractional fund flows are a constant and independent of performance. The alternative is that there is a positive relationship. But, if the alternative is true then this also implies that aggregate fund flows should be larger when larger funds perform relative well. Empirically, the tests conducted here do not lend support to this implication.

Missing, however, from the standard flow-performance model is the fact that individual fund flows have to add up to the aggregate flow each period. Thus, if the aggregate inflow is unusually large then so must be the average fund flow. The converse, of course, must hold as well. A null hypothesis well suited to this environment is one where current market shares fully determine current flows. Thus, if a fund has 1% of all funds under management then it should, under the null, receive 1% of all flows.

Based on the above arguments this paper develops a model that has as its null hypothesis that a fund's market share growth is independent of its return, or at least linear in it. This empirical model is then employed to reexamine the issue of how fund performance impacts future fund market shares. The conclusion reached here is that while the relationship appears to be positive it is not obviously convex.

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11 Appendix: Convexity with Three or More Funds

Suppose aggregate fund flows are independent of the individual funds' relative returns. (This does mean aggregate flows are independent of other market variables. For example, aggregate flows may depend on the prior period's overall market return.) Assume there are at least three mutual funds. A function f is said to be strictly convex if for two points indentified by the vectors R_1 and R_2 one has

$$f\left(\lambda R_1 + (1-\lambda) R_2\right) < \lambda f\left(R_1\right) + (1-\lambda) f\left(R_2\right) \tag{7}$$

for λ between zero and one.

11.1 Dollar Flows Based on Returns

In this subsection assume the mapping from returns to fund flows is via each fund's relative return. For each fund assume there is a mapping from returns to its own dollar flow based on the returns of all funds. Given these assumptions one can write $f_i = f_i\left(r_1, \ldots, r_I\right)$ where r_j is fund j's return. Denote the vector of returns (r_1, . . ., r_I) by R. From the adding up constraint one has $F = \sum f_i$. With this notation in hand one can now prove that the f_i cannot be locally convex (or concave) in returns. In the interest of expositional simplicity the proof of the following proposition is not completely rigorous, but rather contains just the most significant steps. To further simplify matters the proof assumes the set of feasible returns is an open set.

***Proposition 4**: If F is independent of the set of returns then the return-fund flow relationship f_i for fund i cannot be locally strictly convex or concave in the vector of returns R for any feasible set of returns.*

Proof: Consider a set of returns R such that the f_i are locally convex at R. Now consider two vectors of returns R_1 and R_2 inside the convex region and their weighted average $\lambda R_1+(1-\lambda)R_2$ such that $R=\lambda R_1+(1-\lambda)R_2$. (One can show such regions are an open set and thus this pairing is always possible.) If the flow return relationship is locally convex at R then one must have from the definition of a convex function that:

$$\begin{aligned} F\left(\lambda R_1+(1-\lambda)R_2\right) &= \sum_i f_i\left(\lambda R_1+(1-\lambda)R_2\right) \\ &< \sum_i \lambda f_i\left(R_1\right)+(1-\lambda)f_i\left(R_2\right)=\lambda F\left(R_1\right)+(1-\lambda)F\left(R_2\right) \end{aligned} \qquad (8)$$

which violates the condition that F is independent of the return distribution. To prove the proposition for the convex concave case simply note that if the f_i are locally concave the inequality in (8) is reversed which then reverses the inequality in (9). QED.

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12 Tables

Table 1: Market Shares by Category over Time

This table displays market shares by category. The index fund, enhanced index fund, active share values (AS) and tracking error values (TE) are based on Cremers and Petajisto (2009). The data comes from the paper's addenda page on www.sfsrfs.org. Definitions: Very Low AS if AS ≤ 1%, Low AS if 1% < AS ≤ 10%, High AS if AS ≥ 90%. For the tracking error columns, funds are ranked by tracking error and placed into deciles. The aggregate market share of those in the bottom decile is given in the TE D1 column. Similarly the TE D10 column displays the aggregate market share of funds in the top tracking error deciles. The cutoff values used to create the D1 and D10 tracking error deciles are displayed in the TECO D1 and TECO D10 columns respectively.

Year	Index Fund	Enhanced Index Fund	Very Low AS	Low AS	High AS	TE D1	TE D10	TECO D1	TECO D10
			Aggregate Market Share					Cutoff Values	
1991	0.0426	0.02	0.0329	0.0042	0.1379	0.2937	0.0241	0.0327	0.0954
1992	0.0509	0.023	0.0451	0.0007	0.1568	0.1755	0.041	0.0289	0.0922
1993	0.0548	0.0193	0.0387	0.0091	0.1844	0.1847	0.0791	0.0318	0.0868
1994	0.0600	0.0172	0.0399	0.0108	0.1354	0.147	0.0614	0.0278	0.0804
1995	0.0649	0.0147	0.0414	0.014	0.1096	0.1977	0.0886	0.0267	0.092
1996	0.0834	0.013	0.0570	0.0186	0.1087	0.2062	0.0381	0.0278	0.0979
1997	0.0989	0.0131	0.0270	0.0642	0.1178	0.2045	0.0324	0.0324	0.1025
1998	0.1225	0.0155	0.0241	0.0873	0.0788	0.2997	0.0197	0.0397	0.1608
1999	0.1364	0.0167	0.0696	0.0515	0.0572	0.2428	0.0238	0.0358	0.1312
2000	0.1326	0.0206	0.0403	0.0863	0.0522	0.2046	0.0484	0.0418	0.1962
2001	0.1435	0.0189	0.0321	0.1057	0.0598	0.2129	0.0393	0.025	0.1355
2002	0.1484	0.0141	0.0268	0.1153	0.0691	0.2232	0.0691	0.0295	0.127
2003	0.1580	0.0156	0.1044	0.0341	0.0773	0.2044	0.0365	0.0175	0.0771
2004	0.1645	0.0159	0.1063	0.0353	0.0832	0.2328	0.0426	0.0171	0.0718
2005	0.1695	0.0174	0.0939	0.0443	0.0852	0.2032	0.0457	0.0173	0.0628
2006	0.1753	0.0184	0.0769	0.0288	0.1221	0.2324	0.0433	0.021	0.0745

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Table 2: Summary Statistics

Panel A: Summary statistics for the quarterly (1971-2006) and monthly flow data (1991-2006) used in the paper. The first column reports the year followed by the number of funds with sufficient data (non-missing period flow, assets under management, and return information) in the middle of each selected year. The next two columns report the average and *t*-statistics (in parenthesis) for two flow measures found in the prior literature. The $\overline{f_t}$ measure reports the average dollar inflows, in millions of dollars, across funds. The $\overline{f_t / n_{t-1}}$ column presents the period's average flow to lagged funds under management across funds. The Median MS column represents the median market share across funds in a particular period in basis points, i.e. $10000 n_{i,t}/N_t$.

		Quarterly Data							Monthly Data				
		$\overline{f_t}$	$\overline{f_t / n_{t-1}}$	Market Share (bps)					$\overline{f_t}$	$\overline{f_t / n_{t-1}}$	Market Share (bps)		
		(mn)	(%)	10%	Median	90%			(mn)	(%)	10%	Median	90%
1971	208	-1.923	1.52	0.9214	11.661	117.0133	1992	978	4.688	2.862	0.1491	2.0306	23.0066
		(3.65)***	(2.90)***						(7.04)***	(13.07)***			
1976	219	-4.762	-2.502	1.9628	11.805	126.5684	1994	1671	3.695	3.101	0.0425	0.8935	11.5701
		(6.91)***	(11.55)***						(7.44)***	(17.20)***			
1981	241	-2.612	-0.77	2.5759	15.2823	97.1405	1996	2568	3.906	3.548	0.0137	0.3878	7.0817
		(3.00)***	(2.44)**						(5.99)***	(24.02)***			
1986	396	15.468	8.002	0.6957	8.4804	64.5676	1998	3977	3.162	3.882	0.0078	0.2388	4.0525
		(3.69)***	(9.14)***						(6.55)***	(28.37)***			
1991	837	8.69	5.685	0.2103	2.533	28.9421	2000	5173	1.881	2.381	0.0048	0.1543	2.9435
		(5.01)***	(11.32)***						(3.70)***	(22.81)***			
1996	2513	17.777	21.409	0.0113	0.3982	7.038	2002	5574	-1.148	0.238	0.0061	0.1824	2.9958
		(8.03)***	(21.77)***						(3.23)***	(4.73)***			
2001	5467	7.518	8.985	0.0061	0.1627	2.8251	2004	4890	1.545	0.056	0.0127	0.2345	3.4524
		(8.48)***	(29.62)***						(3.32)***	-1.31			
2006	4274	-2.771	-1.286	0.0163	0.2763	3.9798	2006	4263	-2.044	-0.785	0.0159	0.2673	3.9286
		(1.70)*	(11.65)***						(4.21)***	(22.74)***			

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Panel B: Summary statistics for the distribution of the AUM×Rank and the cov(AUM, Rank) variables. The variable AUM equals the assets under management for a fund, and rank is its normalized rank from 0 to 1 based on the performance measure being used.

	Catetory-adjused return-based Ranks						
AUM in $bn	mean	std	10%	25%	50%	75%	90%
Quarterly Data							
Sum(AUM×Rank)	447.00	606.55	17.85	22.06	96.93	803.96	1444.20
Sum(AUM×Rank^2)	300.77	409.69	11.78	14.02	64.10	504.78	966.04
N×cov(AUM, Rank)	17.82	69.35	-13.28	-1.25	1.91	18.13	86.80
N×cov(AUM, Rank^2)	7.25	71.13	-42.80	-3.22	0.51	7.46	61.99
Monthly Data							
Sum(AUM×Rank)	975.89	576.36	191.48	359.46	1100.07	1430.59	1654.73
Sum(AUM×Rank^2)	651.10	388.74	121.11	258.32	739.41	951.19	1110.61
N×cov(AUM, Rank)	24.57	94.40	-84.91	-25.90	15.64	67.55	148.99
N×cov(AUM, Rank^2)	0.20	101.16	-122.38	-55.65	0.00	42.02	125.41

Table 3: **Aggregate Flows Regressed on TAUM-based Measures**

Funds are sorted into 20 groups according to lagged alpha or category-adjusted returns. Next, aggregated flows labeled AggFlow and in units of billions of dollars are regressed on the following models: $F_t / N_{t-1}(\%) = \gamma_1 \sum_i n_{i,t-1} / N_{t-1}(\%) \times k_{i,t-1} + \gamma_2 \sum_i n_{i,t-1} / N_{t-1}(\%) \times k_{i,t-1}{}^2 + \gamma_1 \times I \times \operatorname{cov}\left(n_{i,t-1} / N_{t-1}(\%), k_{i,t-1}\right) + \gamma_2 \times I \times \operatorname{cov}\left(n_{i,t-1} / N_{t-1}(\%), k_{i,t-1}{}^2\right)$, where F_t is the aggregate flow, $n_{i,t-1}$ and $k_{i,t-1}$ are the lagged assets and ranks of each group, $N_{t-1} = \sum_i n_{i,t-1}$ is aggregate total assets, $\operatorname{cov}\left(n_{i,t-1}, k_{i,t-1}\right)$ is the cross-sectional covariance between $n_{i,t-1}$ and $k_{i,t-1}$. The label Sum(n×Rank)/N equals $\sum_i n_{i,t-1} / N_{t-1}(\%) \times k_{i,t-1}$ while Sum(n×Rank^2)/N equals $\sum_i n_{i,t-1} / N_{t-1}(\%) \times k_{i,t-1}^2$. Similarly, the lables I×cov(n, Rank)/N equals $I \times \operatorname{cov}\left(n_{i,t-1} / N_{t-1}(\%), k_{i,t-1}\right)$ and I×cov(n, Rank^2)/N equals $I \times \operatorname{cov}\left(n_{i,t-1} / N_{t-1}(\%), k_{i,t-1}^2\right)$. The variable TAUM is sample's total net assets in billions of dollars. The market return MKT is in fractional values. The *t*-statistics are in parenthesis.

	Alpha-based Ranks						Catetory-adjused return-based Ranks					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
A. Quarterly Data												
Constant	0.0019	-0.0137	0.0003	0.001	-0.0241	-0.001	0.0022	0.0292	0.0039	0.0012	0.0501	0.004
	(2.43)**	(0.45)	(0.14)	(1.38)	(0.77)	(0.43)	(2.49)**	(1.14)	(2.03)**	(1.52)	(1.86)*	(2.27)**
Sum(n×Rank)/N		0.0004			0.0009			-0.0013			-0.0021	
		(0.35)			(0.77)			(1.23)			(1.84)*	
Sum(n×Rank^2)/ N		-0.0002			-0.0007			0.0012			0.0018	
		(0.21)			(0.71)			(1.33)			(1.83)*	
I×cov(n, Rank)/N			0.0004			0.0008			-0.0013			-0.002
			(0.35)			(0.77)			(1.23)			(1.84)*
I×cov(n, Rank^2)/N			-0.0002			-0.0006			0.0012			0.0017
			(0.21)			(0.71)			(1.33)			(1.83)*
MKT				0.0374	0.0376	0.0376				0.0438	0.047	0.047
				(2.75)***	(2.75)***	(2.75)***				(2.99)***	(2.96)***	(2.96)***
Lag_MKT				0.0109	0.0108	0.0108				0.0093	0.0112	0.0112
				(1.11)	(1.11)	(1.11)				(0.84)	(1.02)	(1.02)
Lag_F/N	0.565	0.552	0.552	0.5694	0.5625	0.5625	0.6726	0.6673	0.6673	0.684	0.6663	0.6663
	(5.30)***	(4.74)***	(4.74)***	(6.40)***	(5.73)***	(5.73)***	(7.22)***	(7.07)***	(7.07)***	(9.43)***	(9.04)***	(9.04)***
R-sqrt	0.3112	0.3141	0.3141	0.3952	0.3979	0.3979	0.4438	0.4496	0.4496	0.5195	0.533	0.533
Constant	0.0019	-0.0137	0.0003	0.001	-0.0241	-0.001	0.0022	0.0292	0.0039	0.0012	0.0501	0.004
	(2.43)**	(0.45)	(0.14)	(1.38)	(0.77)	(0.43)	(2.49)**	(1.14)	(2.03)**	(1.52)	(1.86)*	(2.27)**

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Continued:

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
			Alpha-based Ranks						Catetory-adjused return-based Ranks			
B. Monthly Data												
constant	0.0006	0.0098	0.0014	0.0005	-0.0001	0.0005	0.0009	0.0046	0.0011	0.0007	0.0035	0.0009
	(3.21)***	(1.67)*	(3.29)***	(2.45)**	(0.02)	(1.18)	(3.64)***	(1.00)	(2.91)***	(2.81)***	(0.75)	(2.20)**
Sum(n×Rank)/N		-0.0003			0.0001			-0.0001			-0.0001	
		(1.31)			(0.26)			(0.64)			(0.54)	
Sum(n×Rank^2)/N		0.0003			-0.0001			0.0001			0.0001	
		(1.15)			(0.35)			(0.51)			(0.48)	
I×cov(n, Rank)/N			-0.0003			0.0001			-0.0001			-0.0001
			(1.31)			(0.26)			(0.64)			(0.54)
I×cov(n, Rank^2)/N			0.0003			-0.0001			0.0001			0.0001
			(1.15)			(0.35)			(0.51)			(0.48)
MKT				0.0189	0.019	0.019				0.0207	0.0205	0.0205
				(3.77)***	(3.72)***	(3.72)***				(4.26)***	(4.19)***	(4.19)***
Lag_MKT				0.0001	0.0001	0.0001				0.0001	0.0001	0.0001
				(2.15)**	(2.25)**	(2.25)**				(2.12)**	(2.13)**	(2.13)**
Lag_F/N	0.4628	0.4498	0.4498	0.4432	0.444	0.444	0.5205	0.5095	0.5095	0.5206	0.5132	0.5132
	(5.60)***	(5.48)***	(5.48)***	(4.97)***	(5.14)***	(5.14)***	(6.33)***	(6.02)***	(6.02)***	(5.84)***	(5.59)***	(5.59)***
R-sqrt	0.2083	0.2143	0.2143	0.3387	0.3401	0.3401	0.2636	0.2671	0.2671	0.3914	0.3927	0.3927
Constant	0.0006	0.0098	0.0014	0.0005	-0.0001	0.0005	0.0009	0.0046	0.0011	0.0007	0.0035	0.0009
	(3.21)***	(1.67)*	(3.29)***	(2.45)**	(0.02)	(1.18)	(3.64)***	(1.00)	(2.91)***	(2.81)***	(0.75)	(2.20)**

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Table 4: Percentage Flows and Changes in Market Share by Performance Vigintile

This table measures flows via changes in market share via $u_{i,t} = n_{i,t} / N_t - n_{i,t-1} / N_{t-1}$ and $u_{i,t} = f_{i,t} / n_{i,t-1}$. Here, $n_{i,t-1}$, N_{t-1}, $n_{i,t}$, and N_t are lagged and concurrent assets under management for fund *i* in period *t*. The term $f_{i,t}$ is the dollar flow received by fund *i* in period *t*. Each column reports the average value of $u_{i,t}$ for each performance vigintile averaged across months from 1991 to 2008. Only domestic equity funds are included: Lipper Objective Codes EI, EIEI, ELCC, EMN, G, GI, I, LCCE, LCGE, LCVE, LSE, MC, MCCE, MCGE, CMVE, MLCE, MLGE, MLVE, MR, SCCE, SCGE, SCVE, and SG. Each code is then used to define a fund's category for the computation of the category adjusted returns (Cat-adj Ret).

	Changes in market share (bps)		f/n (%)	
Performance	Return	Cat-adj Ret	Return	Cat-adj Ret
1 (=Low)	-2.794	-1.847	-0.049	0.063
2	-2.873	-2.148	0.080	0.065
3	-3.019	-2.156	0.151	0.229
4	-1.677	-1.884	0.370	0.331
5	-2.527	-1.014	0.296	0.415
6	-1.557	-1.424	0.363	0.403
7	-1.210	-1.122	0.433	0.501
8	-1.538	-1.338	0.387	0.423
9	-1.032	-0.833	0.438	0.465
10	-0.284	-0.643	0.527	0.476
11	-0.513	0.048	0.585	0.610
12	0.709	-0.800	0.622	0.503
13	0.927	0.590	0.778	0.740
14	0.588	0.215	0.678	0.731
15	1.380	1.161	0.787	0.766
16	1.392	1.615	0.926	0.895
17	2.817	1.989	1.014	0.964
18	3.238	1.820	1.021	1.051
19	3.444	3.388	1.237	1.280
20 (=High)	4.529	4.383	2.141	2.032

Table 5: Piecewise Estimate of the Rank Change in Market Share Relationship

This table measures both market share changes and flows via $u_{i,t} = n_{i,t} / N_t - n_{i,t-1} / N_{t-1}$ and $f_{i,t} / n_{i,t-1}$ respectively in percentage terms (100×). Assets under management for fund *i* in period *t* equal $n_{i,t}$ and the sum across funds equals N_t. Panel A reports on a regression of market share changes on ranks using the piecewise linear regression: $100u_{i,t} = \alpha + b_1 \times Low_i + b_2 \times Mid_i + b_3 \times High_i + controls + \varepsilon_{i,t}$, where $Low_i = rank_i \times I\{i \in \text{Low Bin}\}$ are the ranks (normalized to be 0.05, 0.1, …, 1) of the low performance bin and zero otherwise ($I\{i \in \text{Low Bin}\}$ is the indicator function), $Mid_i = (rank_i - Max(Low)) \times I\{i \in \text{Mid Bin}\}$, and $High_i = (rank_i - Max(Low) - Max(Mid)) \times I\{i \in High\ \text{Bin}\}$. The three bins are determined as follows: consider the set of all possible 3-group splits of the 20 rank vigintiles. The algorithm then selects the division with the largest average R^2 in the cross-sectional regressions. The Panel reports the time series average of regression parameters as well as the Newey-West adjusted with 3 lags t-statistics. Panel B reports the break points for the three bins.

	Mkt-shr change		f/n	
Performance Measuress	Ret	Cat-adj ret	Ret	Cat-adj ret
A. Piecewise regression parameters and t-statistics				
constant	0.0133	0.0821	0.7981	0.6055
	(0.38)	(2.36)**	(2.69)***	(1.73)*
Low	-0.0095	0.0085	-0.0322	-4.6586
	(1.05)	(0.69)	(0.01)	(1.44)
Mid	-0.0419	0.1579	0.5071	0.5483
	(0.37)	(1.17)	(3.38)***	(3.28)***
High	0.0462	0.2156	15.4362	11.9699
	(0.55)	(1.71)*	(6.51)***	(5.59)***
Cat_flow	-0.0162	-0.051	-0.5617	-0.5385
	(0.68)	(2.00)**	(2.57)**	(1.82)*
Fee	-1.0208	-3.365	3.6864	49.3521
	(0.50)	(1.19)	(0.16)	(1.96)**
LogAge	-0.1167	-0.078	-1.4382	-1.5632
	(4.53)***	(2.59)***	(5.93)***	(5.49)***
LogSize	0.0325	-0.0063	0.3508	0.1302
	(2.95)***	(0.53)	(3.57)***	(1.12)
vol	0.2223	0.7086	1.1479	3.2451
	(0.26)	(0.76)	(0.14)	(0.32)
Turnover	-2.1505	-2.2183	-3.2045	-19.3585
	(1.14)	(0.93)	(0.42)	(0.86)
Lag_u	0.0029	0.0231	0.5152	-0.1473
	(0.08)	(0.54)	(1.33)	(0.36)
B. Piecewise Regression Break Points				
Mid-Low	14	15	1	1
Max-Mid	16	17	18	2

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Table 6: Impact of Return and Return Ranks on Changes in Market Share

This table measures flows via changes in market share via $u_{i,t} = n_{i,t} / N_t - n_{i,t-1} / N_{t-1}$ in percentage terms (100$u_{i,t}$). Here, $n_{i,t-1}$, N_{t-1}, $n_{i,t}$, and N_t are lagged and concurrent assets under management of the fund and of all funds in the sample. The independent variables $Rank_i$ and $Perf_i$ are the ranks (normalized to be 0.05, 0.1, …, 1) and real performances (in percentage terms) of the 20 rank vigintiles, respectively, and g(.) is a function of ranks and performances. The Panel reports the time series average of regression parameters as well as the Newey-West adjusted with 3 lags *t*-statistics. Panel A uses a fund's return net of the market to calculate its performance rank or return. Panel B uses a fund's return net of the average return in its Lipper category.

A. Mkt-share changes to Market Adjusted Return

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	0.0053	-0.0158	-0.0197	0.0248	0.002	0.0049
	(0.17)	(0.50)	(0.51)	(0.78)	(0.07)	(0.13)
Rank	0.0473	0.041	0.0216			
	(2.45)**	(1.70)*	(0.81)			
$Rank^2$		0.045	0.0621			
		(0.94)	(1.22)			
$Rank^3$			0.0876			
			(0.99)			
perf				0.0021	0.0033	0.007
				(0.98)	(1.45)	(1.61)*
$perf^2$					-0.0006	0.0002
					(0.98)	(0.17)
$perf^3$						-0.0001
						(0.46)
Cat_flow	-0.016	-0.0166	0.0015	-0.0156	-0.0181	-0.0011
	(0.80)	(0.71)	(0.06)	(0.78)	(0.85)	(0.05)
Fee	1.4477	0.5013	0.2711	1.2957	0.6716	0.5144
	(0.80)	(0.25)	(0.16)	(0.84)	(0.41)	(0.29)
LogAge	-0.1034	-0.0938	-0.0928	-0.107	-0.1013	-0.0922
	(4.45)***	(3.74)***	(3.72)***	(4.42)***	(3.84)***	(3.58)***
LogSize	0.0265	0.0299	0.0298	0.0274	0.0284	0.0314
	(2.84)***	(3.33)***	(2.84)***	(2.70)***	(2.86)***	(2.85)***
vol	0.5163	0.2423	0.1886	-0.1492	0.3957	-0.2027
	(0.77)	(0.30)	(0.19)	(0.22)	(0.53)	(0.22)
Turnover	-2.2624	-2.236	-2.4059	-1.9285	-2.0899	-2.2367
	(1.14)	(1.14)	(1.15)	(1.13)	(1.12)	(1.11)
Lag_u	-0.0103	-0.0131	-0.0063	0.0002	0.0336	0.0122
	(0.30)	(0.34)	(0.15)	0.00	(0.98)	(0.32)

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Table 6: Continued

This table measures flows via changes in market share via $u_{i,t} = n_{i,t} / N_t - n_{i,t-1} / N_{t-1}$ in percentage terms (100$u_{i,t}$). Here, $n_{i,t-1}$, N_{t-1}, $n_{i,t}$, and N_t are lagged and concurrent assets under management of the fund and of all funds in the sample. The independent variables $Rank_i$ and $Perf_i$ are the ranks (normalized to be 0.05, 0.1, …, 1) and real performances (in percentage terms) of the 20 rank vigintiles, respectively, and g(.) is a function of ranks and performances. The Panel reports the time series average of regression parameters as well as the Newey-West adjusted with 3 lags *t*-statistics. Panel A uses a fund's return net of the market to calculate its performance rank or return. Panel B uses a fund's return net of the average return in its Lipper category.

B. Mkt-share change to Cat-adj Return

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	0.0717	0.0777	0.0923	0.0674	0.0657	0.0818
	(2.64)***	(2.71)***	(2.91)***	(2.20)**	(2.36)**	(2.79)***
Rank	0.0617	0.0598	0.0443			
	(3.36)***	(3.18)***	(1.57)			
Rank^2		-0.046	-0.0719			
		(0.89)	(1.34)			
Rank^3			0.1224			
			(0.82)			
perf				0.0083	0.008	0.0119
				(4.38)***	(4.12)***	(3.77)***
perf^2					-0.0002	0.0001
					(0.31)	(0.07)
perf^3						-0.0003
						(1.16)
Cat_flow	-0.0409	-0.0663	-0.0371	-0.0569	-0.047	-0.0243
	(1.46)	(3.34)***	(1.54)	(2.45)**	(1.92)*	(1.31)
Fee	-0.7928	-0.0192	1.4343	-0.5744	-0.7967	0.4788
	(0.37)	(0.01)	(0.53)	(0.24)	(0.27)	(0.19)
LogAge	-0.0543	-0.0658	-0.0739	-0.0802	-0.0977	-0.0867
	(2.35)**	(2.66)***	(2.66)***	(3.20)***	(3.71)***	(3.32)***
LogSize	-0.0119	-0.0179	-0.0183	-0.0081	-0.0035	-0.0075
	(1.19)	(1.58)	(1.42)	(0.76)	(0.33)	(0.64)
vol	0.6067	1.2987	0.8703	0.8755	0.784	0.8207
	(0.73)	(1.56)	(0.97)	(1.01)	(0.85)	(1.01)
Turnover	-3.071	-2.6257	-3.5006	-2.655	-2.8301	-3.2889
	(1.25)	(1.06)	(1.34)	(1.10)	(1.14)	(1.28)
Lag_u	-0.0098	-0.0124	0.0026	0.0066	0.0186	0.0111
	(0.34)	(0.37)	(0.07)	(0.21)	(0.60)	(0.32)

Table 7: Impact of Return and Return Ranks on Changes in Fractional Flow (f/n)

This table measures flows via changes in market share via $f_{i,t} / n_{i,t-1}$ in percentage terms. Here, $f_{i,t}$ and $n_{i,t-1}$ are concurrent flows and lagged assets under management. The independent variables $Rank_i$ and $Perf_i$ are the ranks (normalized to be 0.05, 0.1, …, 1) and real performances (in percentage terms) of the 20 rank vigintiles, respectively. The Panel reports the time series average of regression parameters as well as the Newey-West adjusted with 3 lags *t*-statistics. Panel A uses a fund's return net of the market to calculate its performance rank or return. Panel B uses a fund's return net of the average return in its Lipper category.

A. *f/n* to Market Adjusted Returns

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	0.816	1.04	1.0912	1.3966	1.4394	1.0294
	(2.28)**	(2.67)***	(2.59)***	(4.29)***	(4.55)***	(2.92)***
Rank	0.8513	0.9014	0.0154			
	(3.79)***	(3.75)***	(0.05)			
Rank^2		1.1789	1.6553			
		(2.32)**	(3.02)***			
Rank^3			7.0867			
			(3.61)***			
perf				0.1765	0.1647	0.113
				(5.36)***	(5.57)***	(2.34)**
perf^2					0.024	0.0361
					(3.01)***	(2.94)***
perf^3						0.0026
						(0.80)
Cat_flow	-0.5698	-0.3878	-0.3582	-0.4927	-0.5216	-0.3598
	(2.92)***	(1.83)*	(1.54)	(2.54)**	(2.59)***	(1.61)*
Fee	45.2223	34.2809	6.1869	29.1621	20.0784	28.1115
	(1.73)*	(1.30)	(0.25)	(1.21)	(0.80)	(1.12)
LogAge	-2.0653	-2.0788	-1.7755	-1.5593	-1.3071	-1.3613
	(7.64)***	(6.98)***	(6.41)***	(6.31)***	(4.70)***	(5.14)***
LogSize	0.4034	0.4554	0.3728	0.2665	0.2876	0.4208
	(3.76)***	(4.21)***	(3.24)***	(2.59)***	(2.70)***	(3.89)***
vol	9.6191	5.6471	3.0943	-4.8494	-10.235	-7.2498
	(1.16)	(0.68)	(0.34)	(0.57)	(1.17)	(0.72)
Turnover	-7.2915	-9.3502	-5.6428	-1.9319	-7.8626	-9.0684
	(0.95)	(0.96)	(0.65)	(0.35)	(0.96)	(0.91)
Lag_u	0.0754	0.1388	0.2433	0.3055	0.1497	0.1561
	(0.21)	(0.40)	(0.67)	(0.83)	(0.38)	(0.41)

Table 7: Continued

This table measures flows via changes in market share via $f_{i,t} / n_{i,t-1}$ in percentage terms. Here, $f_{i,t}$ and $n_{i,t-1}$ are concurrent flows and lagged assets under management. The independent variables $Rank_i$ and $Perf_i$ are the ranks (normalized to be 0.05, 0.1, …, 1) and real performances (in percentage terms) of the 20 rank vigintiles, respectively. The Panel reports the time series average of regression parameters as well as the Newey-West adjusted with 3 lags *t*-statistics. Panel A uses a fund's return net of the market to calculate its performance rank or return. Panel B uses a fund's return net of the average return in its Lipper category.

B. f/n to Cat-adj Return

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	0.2276	0.2629	0.3467	0.6993	0.9135	0.9078
	(0.60)	(0.67)	(0.89)	(2.00)**	(2.65)***	(2.53)**
Rank	1.0239	1.0658	0.4712			
	(5.66)***	(5.24)***	(1.90)*			
Rank^2		-0.4828	-0.5575			
		(0.68)	(0.90)			
Rank^3			5.3266			
			(3.44)***			
perf				0.2116	0.1894	0.1806
				(8.19)***	(7.71)***	(4.15)***
perf^2					0.0173	0.0198
					(2.31)**	(2.05)**
perf^3						0.001
						(0.19)
Cat_flow	-0.6073	-0.5126	-0.2859	-0.5518	-0.3962	-0.2663
	(2.74)***	(2.26)**	(1.05)	(2.62)***	(1.97)**	(1.02)
Fee	77.0436	90.5298	97.7492	75.374	68.27	74.2044
	(3.12)***	(3.33)***	(3.73)***	(3.35)***	(2.87)***	(3.35)***
LogAge	-1.6824	-1.6854	-1.5225	-1.5788	-1.5427	-1.5448
	(6.19)***	(5.81)***	(4.80)***	(5.58)***	(5.62)***	(5.47)***
LogSize	0.1428	0.1316	0.0766	0.0882	0.08	0.1071
	(1.25)	(1.10)	(0.54)	(0.76)	(0.73)	(0.92)
vol	17.8384	19.4581	17.7682	12.5926	7.2532	8.1183
	(1.86)*	(1.92)*	(1.51)	(1.20)	(0.77)	(0.87)
Turnover	-27.4628	-24.2122	-23.0205	-25.2066	-22.7958	-23.2051
	(1.15)	(0.99)	(0.97)	(1.06)	(1.00)	(1.08)
Lag_u	-0.0907	-0.0699	-0.4245	-0.0255	-0.0348	-0.4228
	(0.23)	(0.18)	(1.18)	(0.07)	(0.10)	(1.11)

Table 8: Return and Return Ranks on Changes in Market Share 6 Month Horizons

This table measures flows via changes in market share via $u_{i,t} = n_{i,t}/N_t - n_{i,t-1}/N_{t-1}$ in percentage terms (100$u_{i,t}$). Here, $n_{i,t-1}$, N_{t-1}, $n_{i,t}$, and N_t are lagged and concurrent assets under management of the fund and of all funds in the sample. The independent variables $Rank_i$ and $Perf_i$ are the ranks (normalized to be 0.05, 0.1, …, 1) and real performances (in percentage terms) of the 20 rank vigintiles, respectively, and g(.) is a function of ranks and performances. The Panel reports the time series average of regression parameters as well as the Newey-West adjusted with 3 lags *t*-statistics. Panel A uses a fund's return net of the market to calculate its performance rank or return. Panel B uses a fund's return net of the average return in its Lipper category.

A. Mkt-share changes to Mkt-adj Return C(6, 6)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	-0.2297	-0.228	-0.171	-0.2705	-0.1139	-0.1127
	(1.25)	(1.51)	(1.37)	(1.78)*	(1.13)	(0.82)
Rank	0.6417	0.5344	0.4782			
	(6.68)***	(4.72)***	(3.25)***			
$Rank^2$		0.1895	0.3931			
		(0.74)	(1.37)			
$Rank^3$			1.1447			
			(1.33)			
perf				0.1519	0.1737	0.2351
				(4.95)***	(4.37)***	(3.32)***
$perf^2$					-0.036	-0.072
					(0.96)	(1.73)*
$perf^3$						-0.0159
						(0.55)
Cat_flow	0.0619	-0.058	0.0722	-0.0249	-0.0566	-0.0504
	(0.40)	(0.31)	(0.46)	(0.16)	(0.34)	(0.28)
Fee	24.8993	17.0308	19.8609	21.5341	2.9618	5.2455
	(1.97)**	(1.39)	(1.63)*	(1.43)	(0.19)	(0.29)
LogAge	-0.4117	-0.3313	-0.3245	-0.4752	-0.3869	-0.3727
	(3.59)***	(2.84)***	(2.25)**	(3.05)***	(2.03)**	(1.76)*
LogSize	0.1236	0.1283	0.1296	0.1498	0.1294	0.1282
	(3.61)***	(4.82)***	(3.40)***	(4.06)***	(3.43)***	(3.00)***
vol	-0.6995	-3.5542	-5.2298	5.6677	6.0777	5.576
	(0.11)	(0.61)	(0.98)	(0.84)	(0.94)	(0.59)
Turnover	1.2483	1.1172	0.6751	1.4818	1.5605	0.8874
	(1.17)	(1.28)	(1.34)	(1.06)	(1.15)	(1.19)
Lag_u	0.0101	0.0376	0.063	0.0988	0.0867	0.0456
	(0.20)	(0.89)	(1.92)*	(1.47)	(1.23)	(0.77)

Table 8: Continued

This table measures flows via changes in market share via $u_{i,t} = n_{i,t} / N_t - n_{i,t-1} / N_{t-1}$ in percentage terms ($100u_{i,t}$). Here, $n_{i,t-1}$, N_{t-1}, $n_{i,t}$, and N_t are lagged and concurrent assets under management of the fund and of all funds in the sample. The independent variables $Rank_i$ and $Perf_i$ are the ranks (normalized to be 0.05, 0.1, …, 1) and real performances (in percentage terms) of the 20 rank vigintiles, respectively, and g(.) is a function of ranks and performances. The Panel reports the time series average of regression parameters as well as the Newey-West adjusted with 3 lags *t*-statistics. Panel A uses a fund's return net of the market to calculate its performance rank or return. Panel B uses a fund's return net of the average return in its Lipper category.

B. Mkt-share change to Cat-adj Return C(6,6)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	-0.03	0.0829	0.1412	-0.0218	0.0409	0.179
	(0.13)	(0.30)	(0.50)	(0.09)	(0.14)	(0.59)
Rank	0.704	0.6359	0.5736			
	(7.96)***	(8.58)***	(4.92)***			
$Rank^2$		0.2194	0.1305			
		(0.53)	(0.32)			
$Rank^3$			0.9944			
			(1.94)*			
perf				0.218	0.2281	0.3034
				(9.15)***	(8.19)***	(8.53)***
$perf^2$					0.0054	0.0387
					(0.17)	(1.22)
$perf^3$						-0.0227
						(1.57)
Cat_flow	-0.2307	-0.1343	-0.1223	-0.2313	-0.2102	-0.2196
	(1.46)	(0.57)	(0.59)	(1.58)	(1.01)	(0.94)
Fee	7.6924	-2.2204	1.1768	1.983	2.2966	-6.3159
	(0.68)	(0.17)	(0.09)	(0.16)	(0.15)	(0.42)
LogAge	-0.4208	-0.3135	-0.2804	-0.3835	-0.329	-0.333
	(3.46)***	(2.79)***	(2.12)**	(2.84)***	(2.15)**	(1.97)**
LogSize	0.0004	-0.0231	-0.0466	-0.0034	-0.0297	-0.029
	(0.01)	(0.30)	(0.60)	(0.05)	(0.37)	(0.40)
vol	11.1416	7.2421	7.9882	15.1616	14.2547	10.9267
	(2.14)**	(1.10)	(1.43)	(2.55)**	(2.30)**	(1.68)*
Turnover	0.6157	0.4276	-0.4608	-0.4715	-0.7284	-1.8945
	(1.02)	(0.68)	(0.42)	(0.48)	(0.67)	(0.90)
Lag_u	-0.0038	-0.0248	-0.0308	0.0709	0.0155	-0.0252
	(0.05)	(0.30)	(0.38)	(0.91)	(0.17)	(0.30)

Table 9: Return and Return Ranks on Changes in Fractional Flow (f/n) 6 Month Horizons

This table measures flows via changes in market share via $f_{i,t} / n_{i,t-1}$ in percentage terms. Here, $f_{i,t}$ and $n_{i,t-1}$ are concurrent flows and lagged assets under management. The independent variables $Rank_i$ and $Perf_i$ are the ranks (normalized to be 0.05, 0.1, …, 1) and real performances (in percentage terms) of the 20 rank vigintiles, respectively. The Panel reports the time series average of regression parameters as well as the Newey-West adjusted with 3 lags *t*-statistics. Panel A uses a fund's return net of the market to calculate its performance rank or return. Panel B uses a fund's return net of the average return in its Lipper category.

A. f/n to Mkt-adj Return C(6,6)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	0.5135	2.2192	3.1214	3.8946	6.4942	6.1465
	(0.18)	(0.88)	(1.44)	(2.03)**	(3.79)***	(2.62)***
Rank	13.4896	13.848	7.6142			
	(4.25)***	(4.75)***	(3.75)***			
$Rank^2$		8.032	8.0977			
		(1.75)*	(1.76)*			
$Rank^3$			62.6811			
			(5.66)***			
perf				6.2556	6.8734	5.6689
				(9.26)***	(7.78)***	(5.22)***
$perf^2$					0.031	-0.7401
					(0.09)	(1.03)
$perf^3$						0.4247
						(1.84)*
Cat_flow	-4.997	-4.6738	-3.209	-0.0573	-0.8078	-2.1497
	(1.32)	(1.20)	(0.82)	(0.02)	(0.29)	(0.67)
Fee	495.0902	411.4984	376.6597	383.9247	204.7801	114.6909
	(2.47)**	(2.29)**	(2.22)**	(1.74)*	(0.96)	(0.53)
LogAge	-14.7827	-12.4535	-11.7475	-11.3185	-9.8581	-10.245
	(5.57)***	(5.21)***	(4.84)***	(5.75)***	(3.88)***	(3.96)***
LogSize	4.157	3.8475	2.9989	2.7411	2.4738	2.1934
	(5.34)***	(5.72)***	(4.22)***	(4.02)***	(3.41)***	(2.48)**
vol	-17.9047	-94.4012	-26.8578	70.0885	61.7667	136.8611
	(0.24)	(1.34)	(0.33)	(0.73)	(0.69)	(1.67)*
Turnover	31.65	20.7231	15.2475	32.902	32.7055	15.2945
	(1.12)	(1.17)	(1.31)	(1.07)	(1.09)	(1.19)
Lag_u	1.01	1.3797	0.958	-0.3983	-0.3742	0.5834
	(1.57)	(1.66)*	(1.45)	(0.45)	(0.44)	(0.71)

Table 9: Continued

This table measures flows via changes in market share via $f_{i,t} / n_{i,t-1}$ in percentage terms. Here, $f_{i,t}$ and $n_{i,t-1}$ are concurrent flows and lagged assets under management. The independent variables $Rank_i$ and $Perf_i$ are the ranks (normalized to be 0.05, 0.1, …, 1) and real performances (in percentage terms) of the 20 rank vigintiles, respectively. The Panel reports the time series average of regression parameters as well as the Newey-West adjusted with 3 lags *t*-statistics. Panel A uses a fund's return net of the market to calculate its performance rank or return. Panel B uses a fund's return net of the average return in its Lipper category.

B. f/n to Cat-adj Return C(6,6)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
constant	-0.3156	3.2135	6.4703	1.4541	1.2387	6.507
	(0.09)	(0.62)	(1.13)	(0.41)	(0.33)	(1.37)
Rank	14.9167	14.1424	6.0545			
	(12.24)***	(8.11)***	(2.76)***			
$Rank^2$		10.3657	10.8167			
		(1.29)	(2.00)**			
$Rank^3$			81.018			
			(5.78)***			
perf				7.2056	7.1616	5.7201
				(12.50)***	(11.52)***	(12.33)***
$perf^2$					1.0618	1.2937
					(1.68)*	(1.98)**
$perf^3$						0.9084
						(1.71)*
Cat_flow	-3.8375	-3.3917	-2.7925	-1.3884	0.7852	-0.4666
	(1.06)	(0.67)	(0.56)	(0.51)	(0.22)	(0.11)
Fee	323.0884	44.4416	123.1032	448.6726	270.9604	-161.498
	(2.31)**	(0.27)	(0.76)	(2.73)***	(1.30)	(0.77)
LogAge	-11.7491	-10.6882	-9.608	-9.391	-7.7593	-7.1551
	(3.79)***	(3.13)***	(3.59)***	(4.34)***	(3.17)***	(2.65)***
LogSize	1.6324	1.5505	0.6164	0.5138	1.4169	0.7286
	(1.53)	(1.23)	(0.64)	(0.41)	(1.10)	(0.87)
vol	103.493	83.2226	160.6342	207.7318	136.6113	215.0427
	(0.65)	(0.46)	(1.04)	(1.72)*	(0.96)	(1.62)*
Turnover	44.0074	21.8127	-29.3506	1.1533	-20.7643	-63.6047
	(1.53)	(1.72)*	(0.74)	(0.09)	(0.79)	(0.97)
Lag_u	1.5098	1.5971	0.8628	0.3247	-0.3148	0.423
	(1.29)	(1.18)	(0.63)	(0.26)	(0.24)	(0.30)

Table 10: Early Year Performance, Late Year Volatility and Subsequent Year Market Share Changes: C_0=6, C_1=6, C_2=12

Changes in market share are measured via $u_{i,C2} = n_{i,t}/N_t - n_{i,t-C2}/N_{t-C2}$ in percentage terms (100$u_{i,t}$) in a holding period C2. Here, $n_{i,t-C2}$ and N_{t-C2} are lagged assets under management of the fund and of all the sample funds respectively. In each month, mutual funds are independently double sorted into a 10 by 10 panel according to $Std_{i,C1}$, their realized performance standard deviation in C_1, which is the July through December period right before C_2, and $Perf_{i,C0}$, their realized performance in C_0, which the January through June period just prior to C_1. The table reports on a regression of $u_{i,t}\%$ on both performance and the volatility in the following way: $u_{i,C2}\% = b_1 \times Perf_{i,C0} + b_2 \times Std_{i,C1} + b_3 \times Perf_{i,C0} \times Std_{i,C1} + controls$. Panel A reports the time series average of regression parameters as well as the Newey-West adjusted with 3 lags *t*-statistics when raw return is taken as the performance measure. Panels B replaces $Std_{i,C1}$ by $D\_std = Std_{i,C1} - Std_{i,C0}$.

A. Changes in market share (in C2) on performance (in C0) and std of performance (in C1) double sorted panels.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Performance	Market-Adjusted Return				Category-adjusted Return			
constant	0.0540	0.0192	0.0536	0.0533	-0.0253	-0.0522	-0.0181	-0.0230
	(1.63)*	(0.44)	(1.26)	(1.35)	(0.75)	(1.12)	(0.42)	(0.57)
Perf(C_0)	0.0699		0.0691	0.0745	0.0781		0.0805	0.0767
	(7.51)***		(7.13)***	(5.80)***	(5.30)***		(5.18)***	(7.73)***
Std(C_1)		0.0030	0.0026	0.0066		0.0037	-0.0031	-0.0001
		(0.82)	(0.92)	(1.30)		(0.53)	(0.42)	(0.01)
Std(C_1)*perf				-0.0046				0.0017
				(1.03)				(0.20)
Cat_flow	-0.0962	-0.1613	-0.0919	-0.1154	-0.1581	-0.1223	-0.1545	-0.1262
	(1.25)	(2.03)**	(1.21)	(1.62)*	(5.07)***	(1.87)*	(5.45)***	(4.12)***
Fee	-1.4178	-4.2924	-1.9793	-2.1551	3.8204	0.3380	3.6930	2.9729
	(1.18)	(2.82)***	(1.68)*	(1.71)*	(2.26)**	(0.26)	(1.97)**	(1.57)
LogAge	-0.0572	-0.0975	-0.0628	-0.0708	-0.0550	-0.0859	-0.0574	-0.0637
	(2.70)***	(4.28)***	(3.68)***	(6.17)***	(1.65)*	(2.72)***	(1.62)*	(1.74)*
LogSize	-0.0007	0.0180	0.0006	0.0014	0.0019	0.0227	0.0009	0.0030
	(0.11)	(2.55)**	(0.10)	(0.26)	(0.16)	(2.24)**	(0.07)	(0.26)
vol	1.9540	2.8758	2.2518	2.1739	0.5012	1.3717	0.9365	1.2918
	(2.68)***	(2.47)**	(2.42)**	(2.36)**	(1.16)	(2.06)**	(1.33)	(1.69)*
Turnover	-0.0134	-0.0014	-0.0140	-0.0194	-0.0132	0.0065	-0.0220	-0.0183
	(0.98)	(0.09)	(1.06)	(1.64)*	(0.58)	(0.38)	(0.94)	(0.80)
Lag_u	0.0590	0.1777	0.0515	0.0978	0.1311	0.3021	0.1354	0.1709
	(0.75)	(2.66)***	(0.71)	(1.31)	(3.83)***	(4.92)***	(3.48)***	(3.97)***

Table 10: Continued

Changes in market share are measured via $u_{i,C2} = n_{i,t}/N_t - n_{i,t-C2}/N_{t-C2}$ in percentage terms ($100u_{i,t}$) in a holding period C2. Here, $n_{i,t-C2}$ and N_{t-C2} are lagged assets under management of the fund and of all the sample funds respectively. In each month, mutual funds are independently double sorted into a 10 by 10 panel according to $Std_{i,C1}$, their realized performance standard deviation in C_1, which is the July through December period right before C_2, and $Perf_{i,C0}$, their realized performance in C_0, which the January through June period just prior to C_1. The table reports on a regression of $u_{i,t}\%$ on both performance and the volatility in the following way: $u_{i,C2}\% = b_1 \times Perf_{i,C0} + b_2 \times Std_{i,C1} + b_3 \times Perf_{i,C0} \times Std_{i,C1} + controls$. Panel A reports the time series average of regression parameters as well as the Newey-West adjusted with 3 lags *t*-statistics when raw return is taken as the performance measure. Panels B replaces $Std_{i,C1}$ by $D\_std = Std_{i,C1} - Std_{i,C0}$.

B. Changes in market share (in C2) on performance (in C0) and std (C1) - std (C0) double sorted panels

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Performance	Market-Adjusted Return				Category-adjusted Return			
constant	0.0914	0.0376	0.1104	0.1006	0.0404	0.0155	0.0503	0.0624
	(1.75)*	(0.68)	(2.08)**	(1.95)*	(1.00)	(0.29)	(1.35)	(1.71)*
Perf(C_0)	0.0733		0.0758	0.0742	0.0779		0.0798	0.0812
	(5.25)***		(5.82)***	(6.13)***	(10.05)***		(10.72)***	(11.49)***
ds=Std(C_1)-Std(C_0)		-0.0081	-0.0094	-0.0093		-0.0071	-0.0088	-0.0075
		(1.26)	(1.27)	(1.15)		(1.05)	(1.25)	(1.20)
ds*Perf				-0.0107				-0.0099
				(1.33)				(1.74)*
Cat_flow	0.0307	-0.0851	0.0226	0.0241	-0.1704	-0.1469	-0.1587	-0.1273
	(0.22)	(0.84)	(0.17)	(0.19)	(2.20)**	(1.65)*	(2.05)**	(2.05)**
Fee	1.1040	-1.1447	1.0540	1.3877	-0.2790	-2.2852	-0.1091	-0.4768
	(0.71)	(0.60)	(0.69)	(0.83)	(0.10)	(1.04)	(0.04)	(0.19)
LogAge	-0.0745	-0.1073	-0.0723	-0.0738	-0.0378	-0.0889	-0.0365	-0.0442
	(2.33)**	(2.57)**	(2.23)**	(2.15)**	(1.24)	(2.61)***	(1.10)	(1.42)
LogSize	0.0003	0.0176	-0.0014	-0.0009	-0.0025	0.0212	-0.0043	-0.0043
	(0.02)	(1.10)	(0.10)	(0.07)	(0.22)	(1.71)*	(0.37)	(0.37)
vol	1.6256	2.2257	1.0211	1.0829	0.3678	0.9736	0.3401	0.3470
	(1.42)	(1.84)*	(1.13)	(1.11)	(0.62)	(0.86)	(0.54)	(0.62)
Turnover	-0.0178	-0.0034	-0.0211	-0.0217	0.0144	0.0279	0.0120	0.0205
	(0.77)	(0.17)	(0.89)	(0.96)	(0.45)	(0.89)	(0.38)	(0.72)
Lag_u	0.1376	0.2242	0.1385	0.1336	0.0593	0.2176	0.0533	0.0743
	(1.40)	(2.42)**	(1.42)	(1.41)	(0.93)	(3.53)***	(0.81)	(1.21)