

1. Introduction

Many recent studies analyze the determinants of the behavior of mutual fund investors, concentrating on the relation between net flows to mutual funds and their past performance. This research is of obvious relevance for both mutual fund managers and their regulators. For the managers, it is important to know the factors that determine the total net assets under management, which drive their compensation. The regulators should be aware of existing investor behavior patterns that induce managers to take risk.

The stylized findings indicate a clear positive impact of risk-adjusted as well as raw past performance on subsequent net fund flows (see, e.g., [Ippolito, 1992](#); [Gruber, 1996](#)). This impact lasts for at least three years and seems to be the strongest when considering Jensen's alpha (see [Berkowitz and Kotowitz, 2000](#)). The flow performance relationship appears to be convex, indicating that most flows are attracted by the best performing funds (see, e.g., [Chevalier and Ellison, 1997](#); [Sirri and Tufano, 1998](#)). Moreover, flows into a fund are found to be positively related to the performance of the fund family, measured as average performance within the family (see, e.g., [Ivkovic, 2000](#)) or through the presence of star performers in the family (see [Nanda, Wang, and Zheng, 2004a](#)). [Del Guercio and Tkac \(2001\)](#) document a significant effect of changes in Morningstar ratings on subsequent fund flows. Flows are also directly related to fund visibility, as funds belonging to larger families (see [Sirri and Tufano, 1998](#)) and funds advertising in the financial magazines (see [Jain and Wu, 2000](#)) tend to attract larger flows. [Huang, Wei, and Yan \(2007\)](#) provide a theoretical model and supporting evidence that funds with lower search and participation costs (e.g., funds with higher marketing fees and those belonging to larger and better-performing families) are characterized by a less convex flow performance relationship. [Barber, Odean, and Zheng \(2005\)](#) find that investors react negatively to salient fees such as front loads and brokerage commissions, while 12b1 fees have a positive impact on fund flows. [Nanda, Wang, and Zheng \(2004b\)](#) demonstrate that funds introducing new share classes with lower loads and higher 12b1 fees attract more money due to new investor clienteles characterized by a shorter investment horizon and higher flow performance sensitivity. [Malloy and Zhu \(2004\)](#) find that individual investors in poorer and less educated neighborhoods invest more in high-load funds. [Del Guercio and Tkac \(2002\)](#) document that mutual fund investors use less sophisticated measures of fund performance than pension fund clients. Finally, [Baquero and Verbeek \(2006\)](#) find distinct patterns in the investment and disinvestment decisions of hedge fund investors.

In this paper, we analyze the dynamic structure of the flow performance relationship in the US mutual fund industry at the monthly frequency, using the period spanning the 1990s and the first half of the 2000s. Using a structural model for market beliefs about mutual fund performance and the resulting flows, we infer the probability of updating performance information for different groups of investors. We observe that most investors belong to the types that update information more frequently and use a short performance horizon (from 1 to 12 months). They are likely to be sophisticated investors, as this strategy captures the short-lived persistence in mutual fund performance (e.g., [Bollen and Busse, 2004](#); [Hendricks, Patel, and Zeckhauser, 1993](#)). We find that the probability of an investor updating mutual fund performance information in a given month increased substantially from the 1990s to the 2000s. As a result, we observe striking differences in the

flow performance sensitivity pattern of the 1990s and the 2000s, respectively. In the 1990s, the impact of past performance on flows to an average fund does not decay monotonically. More precisely, the impact on flows of performance six months ago is larger than the impact of more recent performance on these flows. In the 2000s, however, the flow performance sensitivity of an average fund is constant for the first half year and decreasing afterwards. Nevertheless, for a highly marketed fund we still observe a hump-shaped flow performance relationship.

In addition, we find that different types of investors are attracted to different funds characterized by certain combinations of age and marketing fees. In both periods, old funds and funds with high marketing fees attract significantly fewer investors who update performance information frequently. Moreover, when these investors update performance information they use a relatively long horizon to measure performance. This results in an even more pronounced hump-shaped flow performance sensitivity pattern for these old and highly marketed funds. These observations are consistent with the view that the old and highly marketed funds attract primarily small and less sophisticated investors, i.e., the disadvantaged clientele according to Gruber (1996). Nanda, Wang, and Zheng (2004b) come to a similar conclusion about the presence of different investor clienteles, based on the finding that flows to the B and C classes (with higher 12b1 fee and deferred load instead of front load) are more volatile and more sensitive to past performance than flows to the A class of the same fund. Moreover, the average flow performance sensitivity is lower for older funds (in line with, e.g., Chevalier and Ellison, 1997) and for funds with higher marketing fees (contrary to the model in Huang, Wei, and Yan, 2007).¹ Finally, as expected, we do not find any evidence of dynamic structure of the flow performance relationship for index funds. We have investigated possible differences in the flow performance sensitivity for various categories of funds, but these are not present in our data in any significant way.

The structure of the paper is as follows. Section 2 describes the CRSP mutual fund data that we use. It also gives a flexible parametric estimate of the dynamic structure of the impact of past performance on fund flows. From this estimate, the information dissemination lag is already visible. To substantiate our claims, we introduce in Section 3 a more structural model for the way different groups of investors react to past performance. This section also contains our main empirical findings. Section 4 presents a number of robustness results concerning index funds and funds with different investment objectives. Finally, Section 5 concludes.

2. Data and "flow performance relationship

2.1. Data description

The data employed in our analysis come from the CRSP Survivor-Bias Free Mutual Fund Database.² In line with other studies, we concentrate on the sample of diversified US

¹Lynch and Musto (2003) and Berk and Green (2004) also develop theoretical models for the relationship between fund flows and performance, rationalizing the convexity of the flow performance relationship. However, they do not model several types of investors in mutual funds and the resulting differences in the flow performance relationship across these types.

²Source: CRSP, Center for Research in Security Prices. Graduate School of Business, The University of Chicago (2002). Used with permission. All rights reserved. www.crsp.uchicago.edu.

equity funds.³ Since one of the main determinants of fund flows is risk-adjusted performance, index funds are excluded. Our sample period is January 1991 to December 2005, for which we have monthly data on fund flows. The data also include fund starting date, monthly returns, and other fund characteristics, such as front, back, and deferred loads, expense ratio, 12b1 fee, and family identifier. These latter variables are available on an annual frequency only. In our regressions of monthly flows, we used annual fund characteristics as of the last calendar year. In a few cases they were missing and we substituted the value of the corresponding fund characteristic from the previous or the following year. Since we use a five-year horizon for fund performance, our analysis is restricted to funds that have at least five years of return history. Thus, the term *young funds* below refers to funds which exist for little longer than five years. We have annualized monthly returns and flows in order to make our results comparable to existing evidence, which is mainly based on annual data.

As we will see, there were significant temporal changes in the behavior of the investors during the sample period. Therefore, we perform the analysis separately for two subsamples: 1991–2000 and 2001–2005. In this paper these are referred to as the 1990s and the 2000s, respectively. The two periods roughly correspond to the bullish and bearish markets in the US. The number of funds in the sample grows from 379 in 1991 to 1309 in 2000 and over 3000 in 2005. The number of fund month observations in the two subsamples increases from 86119 to 148171.

Table 1 presents descriptive statistics for the funds in our data set. During the sample period, an average fund had a fourteen-year performance record, controlled about \$1 billion of assets, and experienced an in-flow (as defined below) of -1.4% /year. The cross-sectional variation in flows was quite large, ranging from an average 58% out-flow for the bottom quintile to 66% in-flow for the top quintile. This may be partly attributed to the relatively high returns (about 9% p.a.) and volatility (about 22% p.a.) during the sample period. On average, funds charged 1.6% front load and adopted a 1.4% expense ratio, including 0.3% 12b1 fee. The total marketing fees amounted to 0.7%. An average fund family consisted of ten funds and had about \$4.6 billion of assets under control. The major difference between the two subsamples was that mutual funds in the 1990s were characterized by relatively high returns (on average, 16% p.a.) and low volatility (18%/year) and, as a result, attracted higher flows (1.0% p.a.). The 2000s were a much more difficult period for fund management, with low average return (5% p.a.) and high volatility (25% p.a.). Another difference is that an average fund has become somewhat younger (12 years) and partly switched fees from front-load (decreasing from 2.0% to 1.3%) to the expense ratio (increasing from 1.3% to 1.5%).

In line with the literature (see, e.g., Gruber, 1996), net relative flows are defined as a net percentage growth of fund assets

$$f_{i,t} = \frac{TNA_{i,t} - (1 + R_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}}, \quad (1)$$

³We select funds that have either ICDI objective Aggressive Growth, Growth and Income, or Long-Term Growth; or Strategic Insight objective Aggressive Growth, Growth & Income, Growth, Income Growth, Growth MidCap, or Small Company Growth. When both ICDI and Strategic Insight objective codes were missing, we selected funds with Wiesenberger objective Growth and Current Income, Long-Term Growth, Maximum Capital Gains, or Small Capitalization Growth.

Table 1
Summary statistics for the CRSP Mutual Fund data set for the periods January 1991–December 2000 and January 2001–December 2005

Variable	Overall		1992–2000		2001–2005	
	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.
Flow (%)	−1.43	56.17	1.05	54.33	−2.92	57.27
TNA (\$mIn)	990	3709	1272	4057	821	3501
Age (years)	13.79	12.09	16.62	14.21	12.10	10.82
Front load (%)	1.56	2.39	1.96	2.55	1.32	2.29
Expense ratio (%)	1.39	0.91	1.28	0.87	1.45	0.92
12b1-fee (%)	0.31	0.37	0.22	0.31	0.36	0.40
Marketing fee (%)	0.66	0.60	0.59	0.56	0.70	0.63
Family size (#)	10.25	18.85	6.56	10.90	12.46	23.61
Family TNA (\$mIn)	4585	23965	3547	18042	5206	27513
Family age (years)	16.96	17.57	16.33	17.45	17.33	17.64
Category flow (%)	5.06	6.60	8.37	7.13	3.07	6.28
Total risk (%)	22.41	38.11	18.00	9.70	25.05	55.12
Total return (%)	8.94	8.48	15.77	4.50	4.85	10.86
Alpha (%)	−1.02	8.62	−0.76	3.89	−1.17	11.45
Beta market	1.00	0.21	0.97	0.15	1.02	0.25
Beta SMB	0.18	0.38	0.20	0.37	0.16	0.39
Beta HML	0.06	0.41	−0.04	0.31	0.12	0.47
Beta MOM	0.02	0.16	0.02	0.18	0.02	0.15

The units of measurement for the variables are added in parentheses. If applicable, the variables are annualized.

where $TNA_{i,t}$ denotes fund i 's total net assets at the end of month t and $R_{i,t}$ is return of fund i in month t . This definition is based on the assumption that all investor earnings are automatically reinvested in the fund and flows occur at the end of month t . Due to the low autocorrelation in monthly returns, flows occurring at other instances during the month will not bias any of our results. To curb the influence of outliers on the estimates below, we winsorize net relative flows (a dependent variable in our regressions) at the 0.5th and 99.5th percentiles. A similar approach was used in Barber, Odean, and Zheng (2005). Alternative approaches include using a truncated regression and excluding small funds, say, with TNA below \$20 million (see, e.g., Sirri and Tufano, 1998). Our results are qualitatively the same irrespective of the method used. In order to avoid the impact of mergers, we exclude from our data set observations of funds which merged during a given month. Since December and June are the big dividend months, the absolute level of flows may be affected for these two months. However, as we are interested in the delay pattern of the sensitivity of flows with respect to past returns, this is not going to affect our results in a systematic way. Another point of concern might be the survivorship bias still present in the CRSP data set (Elton, Gruber, and Blake, 2001). However, while this may affect the absolute level of estimated fund performance, it is not likely to bias the estimated coefficients that measure the sensitivity of flows with respect to past performance.

As mentioned in the introduction, the focus of the present paper is the dynamic pattern of the impact of past performance on mutual fund flows with the aim of uncovering the underlying process of performance information dissemination. Most studies referred to in the introduction analyze flows at the annual frequency, identifying in fact the average sensitivity of flows to performance over a given year. Several studies such as Nanda, Wang,

and Zheng (2004a) and Huang, Wei, and Yan (2007) investigate flows measured at monthly or quarterly frequency; however, they typically include only one lag of past performance and their focus is not on the lag structure of the flow performance relationship. The paper closest in spirit to ours may be Berkowitz and Kotowitz (2000) who examine the sensitivity of fund flows to the distributed lag of past performance using quarterly data and earlier sample period (from 1981 to 1993). Accordingly, the standard model in this literature specifies net relative flows as a linear function of past performance and a set of control variables, i.e.,

$$\tilde{f}_{i,t} = \alpha_0 + \alpha_1 \tilde{r}_{i,t-1} + \alpha_2^T \mathbf{x}_{i,t-1} + \varepsilon_{i,t}, \quad (2)$$

where $\tilde{r}_{i,t-1}$ is some measure of fund i 's performance up to period $t-1$ and vector $\mathbf{x}_{i,t-1}$ includes control variables such as fund size, age, fees, riskiness, and aggregate flow into the fund's category.

Previous studies use various measures of past fund performance (raw returns, risk-adjusted returns, Jensen's alpha, etc.) at low frequencies. Measuring a fund's past performance by, say, a five-year Jensen's alpha for the purpose of predicting aggregate flows to a given fund implicitly assumes that performance over each of the past sixty months is equally important for investors. However, investors may differ with respect to the period used to assess past performance. This can lead to important differences in the sensitivity of current aggregate flows of a given fund to its performance measured over various lags in the past. In the next section, we discuss this aggregation and its consequences in more detail, but in the present section we model it, for simplicity, by taking the performance measure $\tilde{r}_{i,t}$ as a parametrically, but flexibly, specified weighted average of risk-adjusted returns over the past sixty months. These risk-adjusted returns are defined, following Carhart (1997), on the basis of a four-factor model with the market, size, book-to-market, and one-year momentum factors⁴:

$$R_{i,t}^* := R_{i,t} - R_t^f - \sum_{k=1}^4 \hat{\beta}_i^{(k)} F_t^{(k)}, \quad (3)$$

where $F_t = (R_t^{(m)} - R_t^{(f)}, \text{SMB}_t, \text{HML}_t, \text{MOM}_t)$ denotes the vector of the market return in excess of the risk free rate and returns of the size, book-to-market, and momentum factor-mimicking portfolios. The factor loadings $\beta_i^{(1)}, \dots, \beta_i^{(4)}$ are estimated using the past sixty months of data. Average factor loadings as well as Jensen's alpha, which is not significantly different from zero (see Table 1), are in line with the literature.

2.2. Dynamic pattern in the flow performance relationship

In line with the arguments given above, we study potential differences in the sensitivity of flows to performance over given months by measuring fund i 's performance as

$$\tilde{r}_{i,t} = \sum_{j=1}^{60} w_j R_{i,t-j}^*, \quad (4)$$

⁴We thank Kenneth R. French for the opportunity to use the factor returns provided at his website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). We also performed the analysis using risk-adjusted returns based on the market model and Fama-French three-factor model, which yielded similar conclusions.

for some weights $w_1, \dots, w_{60}$. Note that we examine aggregate flows at the fund level, since we do not dispose of information about (dis)investment decisions of individual (groups of) investors. Therefore, the weights in (4) can be nonconstant because individual investors weigh past returns with lag-dependent weights, because various groups of investors use different equal-weight performance measures, or because of a combination of the two. As a result, different types of funds may have different lag structures for the sensitivity of flows to the past performance. We elaborate on these points in Section 3, where we effectively provide a structural model for the weights $w_1, \dots, w_{60}$.

For expository reasons we impose in the present section a flexible polynomial structure on the weights w_j in (4), with coefficients that in turn depend linearly on fund characteristics. More precisely, we model

$$w_j = \sum_{k=0}^K \sum_{p=0}^{P_k} \theta_{k,p} p! j^{-p} z_{k,t-1} \quad \text{for } j = 1, \dots, 60. \quad (5)$$

Thus z_{t-1} is a vector of fund characteristics that may influence the sensitivity of fund flows to the past performance. Throughout the paper, we assume that z includes a constant, fund age, and total marketing fees defined as the annual 12b1 fee plus one seventh of the sum of front-end, back-end, and deferred loads. Following [Sirri and Tufano \(1998\)](#), we thus assume that the loads are amortized over a seven-year period. The existing evidence suggests that flows to young funds are more sensitive to their recent performance than those to old funds (e.g., [Chevalier and Ellison, 1997](#)) and that fund fees significantly affect their flow performance sensitivity (e.g., [Sirri and Tufano, 1998](#); [Huang, Wei, and Yan, 2007](#)). Hence, $\theta_{0,p}$ effectively determines the lag structure for an average fund, whereas $\theta_{1,p}$ and $\theta_{2,p}$ show how the lag structure is affected by the fund's age and marketing fees, respectively. The empirical results show that polynomials of the order $P = (5, 4, 3)$ and $P = (5, 3, 3)$ suffice for the 1990s and the 2000s, respectively. In order to identify the model (2), we assume that the overall performance sensitivity parameter α_1 is equal to one. If all weights are equal to each other (i.e., $\theta_{k,p} = 0$, $p > 0$), the weighted sum of risk-adjusted returns in (4) will be equal to the fund's Jensen's alpha estimated over a sixty month period.

The vector of control variables $x_{i,t-1}$ that we use in the regressions includes a number of fund characteristics whose impact on flows has been identified in the literature: log size, log age, front load, 12b1 fee, non-12b1 fee, total risk, log of the number of funds in the family, log size and log age of the family, and category flow. The non-12b1 fee is the difference between the expense ratio and percentage 12b1 fee. The total risk is measured as the standard deviation of the past sixty monthly fund returns. The category flow is defined as the net relative flow to a given Strategic Insight category.

From an empirical point of view, one should keep in mind that small funds have extreme relative flows that could dominate OLS estimates. Unless heteroscedasticity-consistent standard errors are computed, inference based on OLS estimates will be biased. For efficiency reasons, we therefore model the variance of the error term and compute weighted least squares estimates. This is also the approach we use when estimating the structural model in Section 3. Throughout the paper, the variance of $\varepsilon_{i,t}$ is modelled as

$$\text{Var}\{\varepsilon_{i,t}\} = \exp(\delta^T x_{i,t-1}), \quad (6)$$

with $x_{i,t-1}$ denoting the control variables described above. The major determinant of the variance of the error term is a fund's size. Our results do not materially change if we model heteroscedasticity using only size. The specification (6) reflects the observation that the disturbances are heteroscedastic, in contrast to the implicit homoskedasticity assumption in most of the literature. In line with standard econometric techniques, the coefficients δ are estimated on the basis of OLS residuals.

The focus of interest in our paper is the lag structure of the impact of past performance on current flows for different types of funds. For the polynomial specification imposed in the present section, the estimated lag structures for an average fund, young and old funds, and funds with high and low marketing fees are given in Fig. 1 for both the 1990s and the

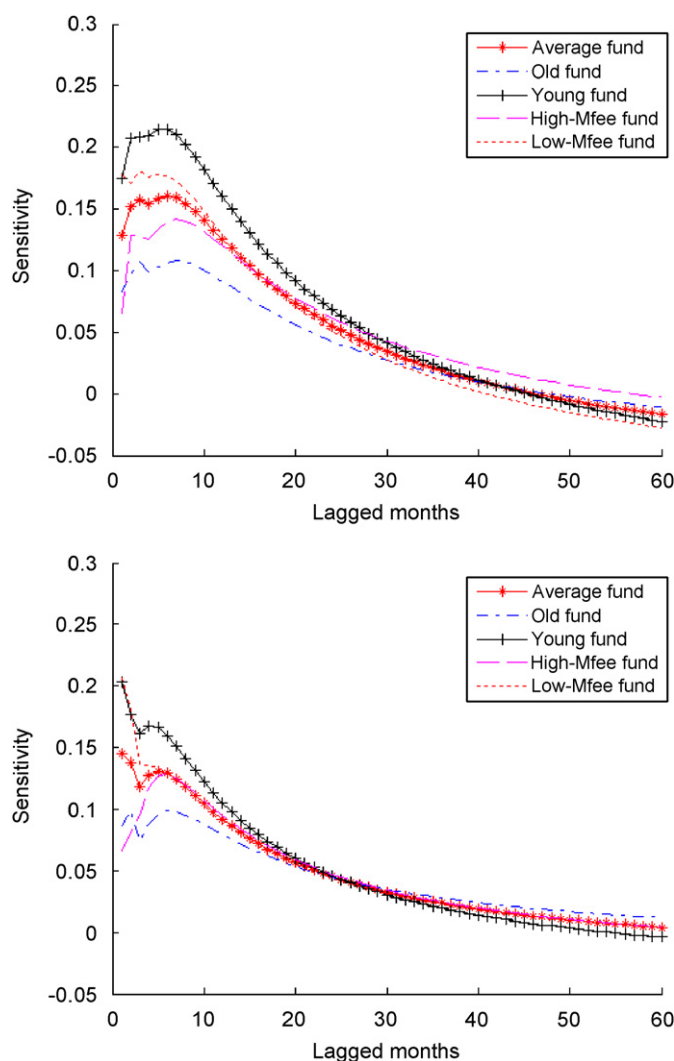


Fig. 1. Dynamic structure flow performance relationship for the 1990s (top panel) and 2000s (bottom panel). The results are based on a flexible reduced form specification as detailed in Section 2.

2000s.⁵ In line with the literature, we find a strong positive impact of past performance on current fund flows. Fig. 1 shows that in the 1990s the flow performance sensitivity of an average fund is hump-shaped, and decreasing for lags larger than six months. It should be noted that both the polynomial specification used here and the structural model in Section 3 imply that the flow performance sensitivity is eventually decreasing although neither specification fixes the starting point of decay exogenously. Moreover, performance over the most recent month is significantly less important than performance from two to eight months ago (e.g., the p-value for the hypothesis that the sensitivity of flows to last-month performance equals that of six months ago is 0.036). On the contrary, in the 2000s (see Fig. 1), the most recent performance has the strongest impact on current flows.

In both subperiods, age and marketing fees have a significant impact on the flow performance sensitivity. The younger the fund, the higher the sensitivity of its flows to performance for every lag. The marketing fees have an opposite impact on the sensitivity of flows to performance over recent periods (decreasing it) and over distant periods (increasing it). As a result, the hump-shaped lag pattern in the flow performance sensitivity in the 1990s is most pronounced for funds with high marketing fees. While the hump-shaped pattern essentially disappeared for average funds in the 2000s, it is still observable for highly marketed funds during that era. For brevity we do not report or discuss the estimates for the control variables here. Since they are close to the estimates in the structural model, their discussion is deferred to the next section.

In the next section, these empirical findings are explained using a structural model for the dissemination of information on mutual fund performance to various investor types.

3. A structural model for information dissemination

The focus of the present paper is to investigate possible causes of the flow performance pattern documented in the previous section. Therefore, we introduce a structural model for market beliefs about the performance of individual mutual funds and the resulting flows. This model is strongly inspired by Carroll (2003), although applied to a completely different context. The model will capture two effects determining the sensitivity of fund flows to their lagged performance. First of all, less sophisticated investors may follow the mutual fund industry less intensively and update their information infrequently. As a result, only a (random) subset of less sophisticated investors reconsiders the portfolio each month and thus on average these investors react to past performance with a lag. The second effect that may play a role is the length of the performance horizon, i.e., the period used by investors to measure past performance (e.g., one quarter, one year, three years, etc.). Bollen and Busse (2004) find that the top decile of funds selected on the basis of past relative risk-adjusted performance generates a statistically significant abnormal return of 25–39 basis points, which disappears after one quarter. In other words, these results show that performance persistence is short-lived, which implies that sophisticated investors use short horizons to assess fund performance.

⁵ Computing the flows for an old fund, we assume that its age is equal to the average in the upper quintile with respect to this variable and that other characteristics are the same as those of an average fund. The patterns for other types of funds are constructed similarly. More precisely, an old fund exists for 33.8 years, a young fund for 5.7 years. A fund with high (low) marketing fees corresponds to a total marketing fee of 1.5% (0.0%).

More formally, consider an arbitrary fund i . Assume that the relevant performance variable in the flow equation (8) is the market belief of future performance of fund i , to be defined below. Consequently, we postulate

$$f_{i,t} = \alpha_0 + \alpha_1 M_{t-1}[R_{i,t}^*] + \alpha_2^T X_{i,t-1} + \varepsilon_{i,t}, \quad (7)$$

where M_{t-1} denotes the market expectation operator (given information available at time $t-1$) applied to future fund performance $R_{i,t}^*$. In order to model the dynamics of $M_{t-1}[R_{i,t}^*]$ consider first the case of a single homogeneous group of investors (further on, we will relax this assumption and extend the analysis to multiple groups of investors).

Following the general idea in [Carroll \(2003\)](#), we assume that $\lambda \in (0, 1)$ is the probability of an investor updating his or her belief about fund i 's performance in a given month. Alternatively, λ can be interpreted as the (wealth-weighted) fraction of investors that updates their beliefs each month. When investors update their performance beliefs, they do so by calculating the average (risk-adjusted) return of fund i over the past H months. As a result, for the expectation conditional on investors updating their performance beliefs, we have

$$M_{t-1}[R_{i,t}^* | \text{update}] = \frac{1}{H} \sum_{h=1}^H R_{i,t-h}^*. \quad (8)$$

However, assuming that only a fraction λ of investors updates their beliefs in a given month and other investors just roll over their performance expectation from last month, the unconditional market-wide expectation satisfies

$$M_{t-1}[R_{i,t}^*] = \lambda \frac{1}{H} \sum_{h=1}^H R_{i,t-h}^* + (1-\lambda) M_{t-2}[R_{i,t-1}^*]. \quad (9)$$

Clearly, the recursive relation (9) induces

$$\begin{aligned} M_{t-1}[R_{i,t}^*] &= \lambda R_{i,t-1}^* / H \\ &\quad + \{\lambda + (1-\lambda)\lambda\} R_{i,t-2}^* / H \\ &\quad + \{\lambda + (1-\lambda)\lambda + (1-\lambda)^2\lambda\} R_{i,t-3}^* / H \\ &\quad + \dots \\ &\quad + \{\lambda + (1-\lambda)\lambda + \dots + (1-\lambda)^{H-1}\lambda\} R_{i,t-H}^* / H \\ &\quad + \{(1-\lambda)\lambda + \dots + (1-\lambda)^{H-1}\lambda + (1-\lambda)^H\lambda\} R_{i,t-H-1}^* / H \\ &\quad + \{(1-\lambda)^2\lambda + \dots + (1-\lambda)^H\lambda + (1-\lambda)^{H+1}\lambda\} R_{i,t-H-2}^* / H \\ &\quad + \dots \\ &= \sum_{j=1}^{\infty} w_j(\lambda, H) R_{i,t-j}^*, \end{aligned}$$

in line with our reduced-form specification (4). The weights w_j depend on the structural parameters λ and H and decrease exponentially to zero as the lag j increases. Note that, by construction, the sum of all weights w_j equals one.

The above specification is based on a single group of homogeneous investors. As we will show, different funds attract different types of investors, each characterized by a specific combination of parameters λ and H . One possible interpretation of these investor types is

that some investors are sophisticated whereas others are unsophisticated. We hypothesize that more sophisticated investors (i) follow the market more closely and thus have a higher probability of update (larger λ) and (ii) use shorter horizons to capture performance persistence (smaller H) in view of the evidence on short-lived performance persistence (Bollen and Busse, 2004; Hendricks, Patel, and Zeckhauser, 1993).

In our empirical specification, we assume that there are three types of investors. The investor types are specified by the parameters $(\lambda_1, H_1 = 1)$, $(\lambda_2, H_2 = 6)$, $(\lambda_3, H_3 = 12)$, i.e., for each type, we fix the horizon H and estimate the monthly update probability λ . We assume that the mass of type k investors attracted to fund i at time t , γ_{ikt} , is positive and determined as an exponential function of selected fund characteristics z including a constant, fund age, and total marketing fees:

$$\gamma_{ikt} = \exp(v_k z_{i,t-1}). \quad (10)$$

The resulting overall performance-related component of fund i shows at time t is given by

$$\alpha_1 M_{t-1}[R_{i,t}^*] = \sum_{k=1}^3 \sum_{j=1}^{\infty} \exp(v_k z_{i,t-1}) w_j(\lambda_k, H_k) R_{t-j}^*. \quad (11)$$

The above inner sum is truncated at $j = 60$ lags in the actual estimation. Finally, note that we could have added an error to Eq. (10) at no cost, as such error would simply be subsumed by the error term in (7). Moreover, note that if actual investors use daily returns to assess performance, this also would not affect the regression coefficients of interest.

Clearly, our choice of three investor groups with, respectively, one, six, and twelve month performance horizons is somewhat arbitrary. First of all, increasing the number of types does not improve the fit of the model to our data in a significant way. Moreover, although we did not formally maximize the likelihood over all triples of integers, alternative specifications of the three horizons lead to a decrease in the likelihood, while the conclusions presented below remain equally valid.

The estimation results based on the model (7) with performance measure (11) are reported in Table 2. We observe that the probability of update is in general negatively related to the length of the performance horizon of a given investor type. For the 2000s the hypothesis that all three λ s are equal is rejected. In other words, more active investors who update their information frequently typically use a shorter performance horizon. These are likely to be sophisticated investors, as this strategy captures the short-lived persistence in mutual fund performance (e.g., Bollen and Busse, 2004). In the 1990s, the probability of update for investors using a one or six-month horizon when updating, is around 7–8%. This is almost twice as big as the probability corresponding to the one-year horizon. In the 2000s, possibly because of a more extensive coverage of the mutual fund industry in the media, the probability of updating performance information for investors with one and six month horizons has more than doubled to 20% and 15%, respectively, whereas for those with the longest horizon has even decreased.

The effects of age and marketing fees on the flow performance sensitivity pattern do come out significantly in our analysis, as the hypothesis that the corresponding coefficients are jointly zero is rejected, both for the 1990s and the 2000s (all p -values are smaller than 0.01). This leads to the specific dynamic flow performance sensitivity patterns for different types of funds presented in Fig. 2. The flow performance sensitivity pattern for an average fund is hump-shaped and peaks around a lag of six months in the 1990s. For the 2000s, it is

Table 2

Estimation results for the structural model (11) both for the 1990s and the 2000s

Coefficient	1992–2000		2001–2005	
	Estimate	Std.err.	Estimate	Std.err.
Constant	−13.13	1.57	−4.71	1.55
Log fund size	−0.46	0.16	−1.78	0.12
Log fund age	−3.52	0.36	−4.99	0.39
Front load	0.21	0.07	1.28	0.08
12b1-fee	5.72	0.63	−7.47	0.51
Non 12b1-fee	4.28	0.25	1.12	0.23
Fund risk	−0.18	0.02	0.00	0.01
Log funds in family	−1.91	0.28	−5.00	0.28
Log family size	1.82	0.20	3.38	0.19
Log family age	1.75	0.34	0.02	0.31
Category dummies	0.69	0.02	0.57	0.02
Type H = 1				
λ	0.07	0.03	0.20	0.06
γ_{const}	1.79	0.52	0.84	0.39
γ_{age}	−0.51	0.10	−0.49	0.12
γ_{fee}	−0.28	0.10	−0.53	0.09
Type H = 6				
λ	0.08	0.04	0.15	0.02
γ_{const}	−0.59	0.77	−1.76	0.65
γ_{age}	−0.45	0.18	−0.34	0.17
γ_{fee}	−0.91	0.41	0.31	0.22
Type H = 12				
λ	0.05	0.01	0.03	0.00
γ_{const}	−2.92	0.67	−2.18	0.15
γ_{age}	−0.02	0.11	0.06	0.06
γ_{fee}	0.86	0.22	0.17	0.05
R ²	0.13		0.38	

characterized by virtually constant weights during the first six months followed by monotonically decreasing weights for longer lags. Young funds and funds with low marketing fees attract significantly more investors with a short performance horizon than their counterparts. This effect is especially pronounced in the 1990s. During this period, flows to young funds are more than twice as sensitive to their performance over the last year than those to old funds; the sensitivities slowly converge to each other by the end of the fifth year. Highly marketed funds enjoy substantially higher flow performance sensitivity for years two to five at the expense of lower sensitivity for the most recent year, compared to funds with low marketing fees.

In the 2000s, the differences are limited to the most recent year; after a one-year lag, flows to different types of funds are equally sensitive to their past performance. Current flows to young and less marketed funds are very sensitive to their most recent performance, especially over the last month. Since highly marketed funds may attract fewer investors with a one-month performance horizon, the dynamic flow performance

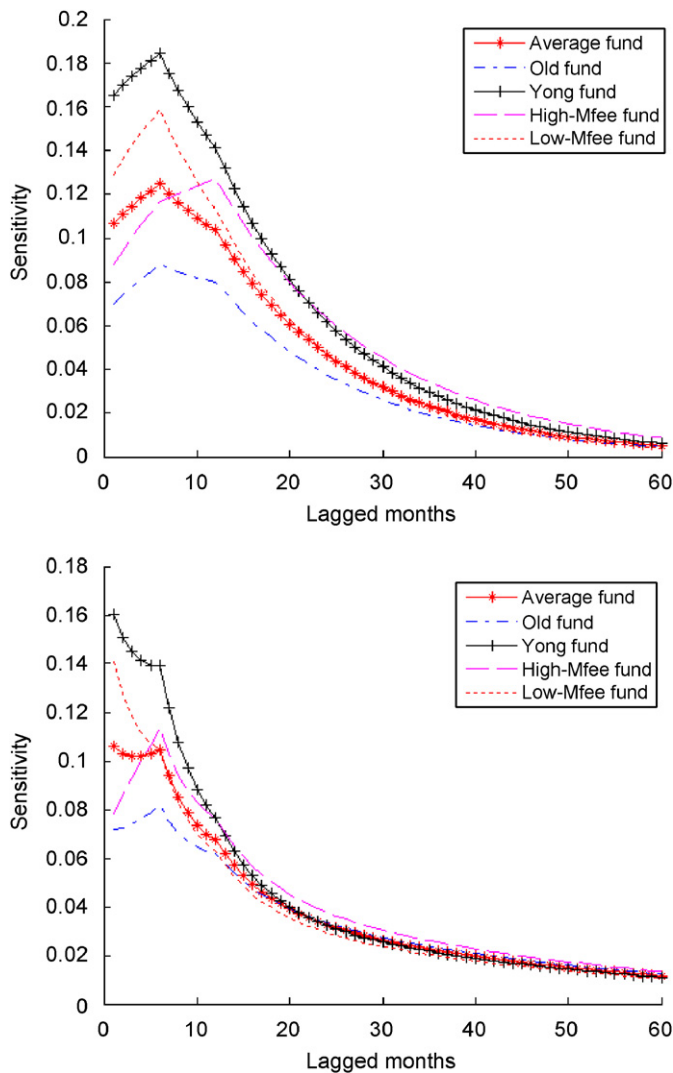


Fig. 2. Dynamic structure flow performance relationship for the 1990s (top panel) and 2000s (bottom panel). The results are based on the structural model presented in Section 3.

pattern is hump-shaped, as the sensitivity of flows to past performance starts to decline only after the sixth lag. Note that all these findings are also visible from the reduced form estimation of Section 2 (see Fig. 1).

The coefficients on the control variables in Table 2 show that larger and older funds have, ceteris paribus, smaller relative flows. This is in line with the findings in, e.g., Sirri and Tufano (1998). Concentrating on the statistically significant estimates, we see that front-end load has a positive effect on fund flows, demonstrating the effectiveness of marketing efforts. Yet, the relation between fund flows and 12b1-fee, which is also used to promote funds, changes from positive in the 1990s, which is in line with Barber, Odean, and Zheng (2005), to negative in the 2000s. The non-12b1-fee affects fund flows positively,

which could be due to investors chasing better-performing funds that may charge a higher management fee. Having more funds in a given family results in smaller flows, which is in line with [Nanda, Wang, and Zheng \(2004a\)](#), yet being part of a larger (in terms of assets) and older family implies larger flows. Interestingly, [Chen, Hong, Huang, and Kubik \(2004\)](#) indeed find that larger family size does not erode performance; however, [Ivkovic \(2000\)](#) documents a negative effect of family age on family flows. As expected and in line with the literature, larger flows to the funds category are associated with larger flows into the individual fund.

The estimation results in this section also provide information on the (wealth-weighted) percentage of investors of a given type. The estimated percentages are presented in [Table 3](#). These estimates confirm the intuition above: investors that follow the market more closely base their performance estimates on shorter horizons and are mostly attracted to the hardly marketed funds. In the 1990s, about 88% of the investors of an average fund used a one-month horizon with a monthly update probability of 7%. In this period, 6% used six-month horizons with a similar update probability of 8%. However, another 6% used a one-year horizon with a somewhat smaller update probability of 5%. The differences are more pronounced for the 2000s. A smaller fraction of the investors uses a one or six-month horizon (78% compared to 94% for the 1990s), but with a much larger probability of update (20% and 15%, respectively). At the same time, about 22% of investors in the 2000s used one-year horizons with a somewhat smaller probability of update as in the 1990s (3% instead of 5%). Alternatively, the considerable increase in the probability of update in the 2000s leads to a much higher flow impact of the most recent performance. Finally, in both subperiods, old and highly marketed funds attract a lower percentage of

Table 3

Monthly probability of investors updating performance information and the fraction of investors attracted to various funds

	H = 1	H = 6	H = 12
1992–2000			
Update probability (%)	7.0	7.9	4.7
Average fund (%)	87.6	6.3	6.1
Old fund (%)	84.5	6.4	9.0
Young fund (%)	89.9	6.1	4.0
Highly marketed fund (%)	81.8	3.5	14.8
Hardly marketed fund (%)	87.6	9.5	2.9
2001–2005			
Update probability (%)	20.0	15.4	2.5
Average fund (%)	65.9	12.5	21.6
Old fund (%)	57.2	12.4	30.3
Young fund (%)	73.2	12.2	14.6
Highly marketed fund (%)	50.6	19.6	29.8
Hardly marketed fund (%)	75.9	8.3	15.8

The three types of investors are characterized by the performance horizon H they use when updating performance information, see (8). For each type and sample period, the row 'Update probability' gives the probability that any given investor of this type updates the mutual fund performance information in any given month, see (9). The rows 'Average', 'Old', 'Young', 'Highly marketed', and 'Hardly marketed' give the average (over the relevant sample period) mass of investors of each type attracted to those funds, see (10). Section 3 contains more details.

the shortest-horizon investors and, in addition, have lower average flow performance sensitivity. Once more, the effects are most pronounced in the 2000s.

4. Robustness studies

Two obvious questions concerning the reaction of mutual fund flows to past performance come to mind. First of all, one may expect that flows to index funds will be insensitive to their past performance, as they do not propagate active management. Given the small number of available index funds, we only consider estimation of the flow performance sensitivity pattern using the fifth-order polynomial weights as in (5). The estimation results (unreported, but available upon request) show no significant dynamic pattern.

Secondly, one may wonder whether the observed patterns vary across funds with different objectives. We estimated the model (2) with performance measure (4) and polynomial structure (5) for the following combinations of Strategic Insight categories: (i) aggressive growth and small company growth, (ii) growth and growth midcap, and (iii) growth/income and income. The results are qualitatively similar for all three investment categories. One may observe a larger impact of more recent performance for the aggressive growth/small company growth category, but this effect is not significant.

5. Summary and concluding remarks

We document a lower sensitivity of flows to mutual funds to very recent performance than to performance half a year or more ago. We attribute this result to the existence of less sophisticated investors who follow the market less closely. This interpretation is based on the estimation of a structural model incorporating three different groups of investors. We find that investors who update performance information infrequently are primarily attracted to highly marketed funds. Moreover, when these investors update performance information, they use a relatively long horizon to measure past performance, which is not in line with the existing evidence on short-lived performance persistence.

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