Market Frictions, Investor Sophistication and Persistence in Mutual Fund Performance*

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Abstract

If there are diseconomies of scale in asset management, any predictability in mutual fund performance will be arbitraged away by rational investors seeking funds with the highest expected performance (Berk and Green, 2004). In contrast, the performance of US equity mutual funds persists through time. In this paper, we report evidence that persistence is less prevalent among hard-to-find funds and investigate whether market frictions can reconcile the assumptions of investor rationality and diseconomies of scale with the empirical evidence. In particular, we extend the setting of Berk and Green (2004) to include entry costs and account for investor heterogeneity in financial sophistication, which we model as differences in reservation returns and the degree of financial constrainedness across investors. We show that for low levels of managerial skill, more visible funds, which are available to a broad set of investors, underperform less visible funds, which are only available to the most sophisticated investors. As managerial skill rises, funds with less sophisticated investors can outperform funds with more sophisticated investors, as a consequence of the interaction of entry costs with financial constraints. Therefore, for a range of managerial skill, hard-to-find funds exhibit less dispersion in equilibrium expected performance. Using data on US equity mutual funds in the 1996-2010 period and different proxies for fund visibility, we find empirical evidence that differences in observed performance are significantly less persistent among hard-to-find funds than otherwise similar funds.

JEL codes: G2; G23.
Keywords: mutual fund performance persistence; market frictions; investor sophistication.

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1 Introduction

Like investors in other retail financial markets, mutual fund investors face non-negligible search costs, entry costs, and switching costs, and are likely to be financially constrained. While the role of market frictions on investor choices has received some attention in the mutual fund literature, the implications of frictions for the determination of mutual fund performance are still not well understood. In this paper, we investigate how market frictions shape investors' investment and disinvestment decisions and the determination of mutual fund performance in equilibrium.

The starting point of our analysis is the model of Berk and Green (BG) (2004), who characterize the competitive provision of capital to mutual funds. In their model, investors learn about managerial ability from past returns and demand shares of all funds with expected risk-adjusted performance net of fees and other costs higher than their reservation return, which is assumed to be zero. In the presence of diseconomies of scale, the flows of money into (out of) outperforming (underperforming) funds drive their performance down (up) to zero. In equilibrium, all funds deliver zero net expected performance. Therefore, fund performance is not predictable from fund characteristics or past performance.

BG's influential work has changed the prevalent view on mutual fund performance persistence by showing that lack of predictability in mutual fund performance is consistent with a market populated by competing rational investors. However, there exists abundant empirical evidence that underperforming US equity funds continue to underperform in the long term (e.g., Carhart, 1997). The model cannot explain, either, why performance persists for winners in the short term (Bollen and Busse, 2005). Therefore, under the framework of BG, the well documented persistence in mutual fund performance is an anomaly that needs to be explained.

One possible explanation for the discrepancy between the model's implication of unpredictability of fund performance and the empirical evidence on performance persistence is that the assumption of diseconomies of scale in asset management is not a good characterization of the mutual fund industry. There exists, however, empirical evidence that US equity fund performance decreases with size. Chen et al. (2004) show that, conditional on other fund characteristics, performance decreases with lagged assets under management, especially for funds investing in small-cap growth stocks, suggesting that liquidity is a source of diseconomies of scale portfolio management. Yan et al. (2008) confirm these findings using more direct measures of portfolio liquidity.

An alternative explanation is that flows of money do not affect fund performance by an amount sufficient to eliminate differences in expected performance. Consistently with this explanation, Bessler et al. (2010) show that outflows from underperforming funds alone cannot eliminate their performance disadvantage.[1] Reuter and Zitzewitz (2010) study the effect of fund flows on performance using a regression discontinuity approach and estimate diseconomies of scale of a magnitude larger than estimated in standard regression but insufficient to eliminate performance persistence. This explanation raises the question of what prevents investor money from flowing freely into and out of funds in response to differences in expected performance. A natural answer to this question is that market frictions such as search costs, switching costs, and liquidity constraints, distort investor choices and limit entry to and exit from mutual funds as a response to differential performance.

The effect of market frictions in general, and search costs in particular, on investor decisions has been previously investigated by the mutual fund literature, in the context of studies of mutual fund flows. Sirri and Tufano (1998) are the first to show that search costs affect investor decisions. In particular, they find that the flow-performance relation is less steep for funds associated with higher search costs. Huang et al. (2007) propose a model in which search costs combined with Bayesian learning from past returns lead investors to consider only funds with the highest recent performance since the costs of researching a new fund with less than top recent performance outweight the expected benefits. More recently, Navone (2012) shows that the sensitivity of flows to past performance decreases with past performance but increases with different proxies for fund visibility.

If performance persistence can be explained by lack of sensitivity of flows to performance, we would expect performance persistence to increase with fund visibility, since the literature has shown that flows of money to more visible funds are more responsive to past performance. To explore this hypothesis, we rank US equity mutual funds every month in the 1996-2010 period according to Carhart's (1997) four-factor alpha over the previous 12 months and allocate funds into ten decile portfolios.[2] We then split the sample according to the value of lagged assets managed by the fund's family. In particular, we create three subsamples: low-visibility funds (family size in the bottom quartile); medium-visibility funds (family size in the second and third quartiles); and high-visibility funds (family size in the top quartile). Finally, we compute the mean four-factor alpha over the subsequent 12 months for funds in each subsample and each decile portfolio. Figure 1 shows the results graphically. Consistently with results from previous studies, identifying future winners by looking at past performance is a difficult thing to do, although past losers continue to underperform. However, what is striking about Figure 1 is the fact that funds in the low-visibility fund subsample do not appear to exhibit more persistence in performance. In fact, performance persistence is less prevalent for this group of funds than for the other two: The difference in performance between last year's top and bottom performers is 1.1% for funds in

[1] They do find, however, that outflows from underperforming funds combined with manager replacement can cause reversals in performance.

[2] In section 3, we provide more detailed information on the dataset and on the construction of our proxy for performance.

the low-visibility subsample, as opposed to 1.75% and 2.32% for funds in the high- and medium-visibility subsamples, respectively. Moreover, low-visibility funds in the bottom performance decile outperform high- and medium-visibility funds with bottom performance by 1% and 0.7%, respectively. In section 4, we show that the lower persistence of mutual fund performance among hard-to-find funds is statistically significant and holds conditional on fund characteristics that have been shown to affect performance, as well as for other proxies of fund visibility. Therefore, contrary to our expectations, fund visibility does not seem to be associated with lower but *higher* performance persistence.

Why do recent losers perform worse if funds are under the scrutiny of thousands of investors, fund analysts and the media? Why do winners with low visibility fail to exhibit the best subsequent performance if these funds are hidden from the public? In other words, why do hard-to-find funds exhibit less performance persistence despite the low flow-to-performance sensitivity documented for these funds?

In this paper, we provide an answer to these questions based on a simple intuition: While fund visibility may increase the amount of available information about a fund's quality and the sensitivity of the fund's flows to its past performance, visibility also changes the composition of a fund's investor base. When a mutual fund family's offerings become more visible, the cost of obtaining information about those funds decreases. This reduction in information costs has the effect of making the funds available to investors who otherwise would not have been aware of their existence or would have not collected information necessary to consider those funds for investment. Such investors are precisely the ones facing the highest search costs and other frictions. We focus on this selection effect and show theoretically that fund visibility has crucial consequences for the determination of performance in equilibrium. More specifically, we develop a model of performance determination that extends the model of BG in several directions. First, we assume that investors' reservation risk-adjusted expected returns are negative for many investors, unlike in the model of BG. Our assumption of negative reservation returns can be justified by the abundant empirical evidence that the average actively managed equity fund underperforms passive benchmarks after fees and trading costs. The assumption of negative reservation returns is also realistic if the investment alternative is an index fund, since risk-adjusted returns for such funds are negative after expenses. More specifically, Hortaçsu and Syverson (2004) report evidence of large dispersion in fees across funds tracking the same benchmark index with some funds charging more than 200 basis points per annum. The authors attribute dispersion in indexed fund fees to search costs. We allow reservation returns to vary across investors to reflect heterogeneity in investor financial sophistication due to differences in education, financial literacy, experience, or intelligence.

Second, we assume that investors are financially constrained, i.e., they face a limit on the amount of money they can invest in a mutual fund each period. Moreover, investors face the risk of not having access to financing sources or suffering from liquidity shocks, which would prevent them from investing

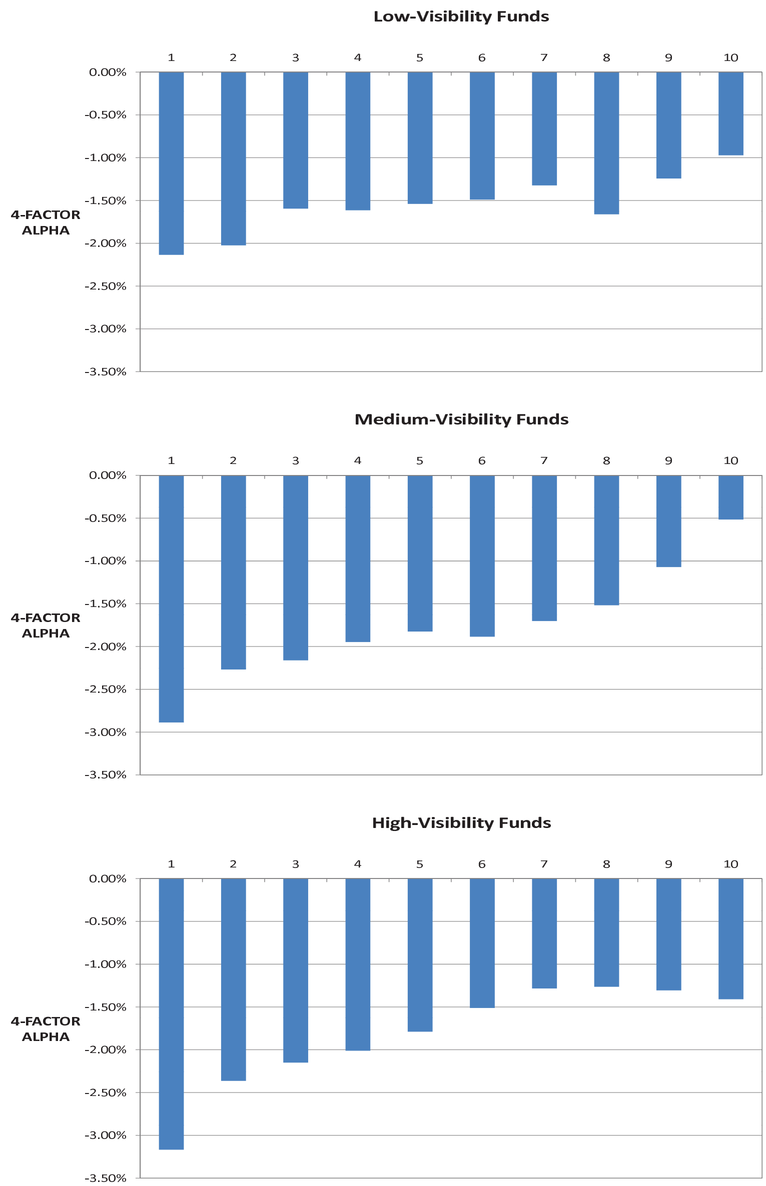

Figure 1: Fund visibility and performance persistence. US equity mutual funds are ranked every month in the 1996-2010 period according to their four-factor alpha over the previous year and allocated into ten decile portfolios, labeled from 1 (bottom) to 10 (top). The sample is then split according to the lagged value of assets managed by the fund's family into three subsamples: low-visibility funds (family size in the bottom quartile); medium-visibility funds (family size in the second and third quartiles); and high-visibility funds (family size in the top quartile). The graphs show mean four-factor alphas measured over the subsequent 12 months.

in a mutual fund. We assume further that this risk is higher for unsophisticated investors.

Third, we assume that investing in a mutual fund for the first time entails an entry cost, which can be thought of as reflecting participation costs.

In each period, investors must decide between investing their money in an actively managed fund and an index fund. Because of search costs, investors earn a negative return on the index fund. In equilibrium, any actively managed fund that stays in business offers an expected net (risk-adjusted) return at least as high as the reservation return of the most sophisticated investor who decides to stay in the fund. If managerial skill is low, only funds targeted to unsophisticated investors can operate since these investors have lower reservation returns. Therefore, unlike in the model of BG, a fund's expected performance can be negative in equilibrium. Moreover, for the same level of managerial skill and fees, more visible funds, whose target investors are on average less sophisticated, capture more assets and, therefore, perform worse than funds targeted to more sophisticated investors. Therefore, investor heterogeneity translates into differences in performance in the cross section of mutual funds.

As managerial skill improves, more of the funds' current investors choose to reinvest with their fund and fewer current investors decide to leave, which increases the fund's assets and makes the fund's performance grow slowly with managerial skill. Eventually, all current investors reinvest their available money with the fund. At this point, new, more sophisticated investors may decide to enter the fund. However, such investors may be deterred by entry costs, in which case, the fund's expected performance will increase one-to-one with managerial skill and may even become positive. Since unsophisticated investors invest less money per capita than sophisticated investors, for sufficiently high entry costs there exists a range of managerial skill such that funds targeted to unsophisticated investors outperform funds sold to sophisticated investors.

For a very high level of managerial skill, all investors in the economy invest with the fund under the assumption that investors' maximum reservation returns are bounded by zero. Since funds targeted to unsophisticated investors have a larger potential investor base, they will be larger and will exhibit poorer performance than funds targeted to more sophisticated investors.

Therefore, the model predicts that the differences in performance across past performance decile portfolios reported in Figure 1 could reflect differences in equilibrium expected performance, rather than lack of investors' response to past performance. Moreover, the analysis also indicates that visible funds, which are available to–and held by–less sophisticated investors, will underperform otherwise identical funds when managerial ability is low but may outperform for higher levels of managerial skill. Therefore, with similar distributions of managerial skill, more visible funds should exhibit higher cross-sectional dispersion in fund expected performance and, hence, more persistent differences in realized performance.

We use US mutual fund equity data in the 1996-2010 period to test the model predictions. We proxy for fund visibility using the size, age and diversity of investment categories of the fund's family. Our proxies are justified by previous research on fund flows, but also by the belief that funds belonging to younger, smaller and less diverse families are harder to find, and therefore, lie outside the investment opportunity set of investors facing high search costs. Indeed, we show that such funds are smaller and charge lower marketing fees. We also use advertising expenditures at the family level to identify funds that target more or less sophisticated investors.

Measuring both past and future performance using the four-factor model of Carhart (1997), we find strong evidence of performance persistence over a one-year period, conditional on observable fund characteristics. However, consistently with our theoretical prediction and with the unconditional analysis of Figure 1, the hardest-to-find funds exhibit significantly less persistence in performance than the rest of funds. This is true for both underperformance and outperformance. Funds whose past performance has been in the bottom decile of the distribution in the last twelve months and which belong to the group of hard-to-find funds, perform not significantly worse than funds with median past performance and significantly better than the rest of recent losers. Similarly, the performance of hard-to-find recent winners is not significantly better than that of the median fund and significantly worse than that of other recent winners. In sum, unlike for all the other funds, we find little evidence of performance persistence for funds in the low-visibility group. When past performance is measured using raw returns, we only find evidence of performance differences between the worst recent performers and the median fund. Again, hard-to-find funds exhibit no evidence of performance persistence.

Results are somewhat different when we use advertising expenditures to proxy for the fund's investor target. While funds with no advertising expenditure exhibit less performance persistence, this result is entirely due to differences among outperforming funds, not underperforming funds.

Finally, the differences between low-visibility and high-visibility funds documented in the paper do not simply capture differences between institutional and retail funds.

Therefore, our empirical results confirm those of the unconditional analysis and lend support to the hypothesis that hard-to-find funds exhibit smaller differences in equilibrium expected performance and, therefore, less persistent performance.

Our paper belongs to a relatively new line of research that investigates the determinants of mutual fund performance persistence in light of Berk and Green (2004) theory. This line of research includes the studies of Ferreira et al. (2010), Elton et al. (2001), Berk and Tonks (2007), and Glode et al. (2011), in addition to the work of Bessler et al. (2010), cited above. Ferreira et al. (2010) study differences in performance persistence across countries and find that such differences are associated with differences in the degree of diseconomies of scale and fund competition. Elton et al. (2011) argue that if there are diseconomies of scale in asset management, then performance should be less persistent among larger funds for which diseconomies of scale are more likely to be important. However, when they divide a sample of equity mutual funds into groups according to assets under management, they find that the degree of performance persistence is similar across all size groups.[3]

Our paper is more closely related to that of Berk and Tonks (2007), who investigate cross-sectional differences in performance persistence for US equity funds. The authors argue that differences in the speed of learning across investors cause the composition of a fund's investor base to change with performance, since the first investors to leave or enter a fund are those who update their beliefs the fastest. As a consequence, remaining investors of a fund that has underperformed in the past have a lower flow-to-performance sensitivity, which prevents the fund's assets from shrinking should the fund continue to underperform in the future. Our paper is also related to the work of Glode et al. (2011). These authors study time variation in performance persistence and find evidence that mutual fund performance persistence is strongest following periods of high market returns and vanishes after periods of low market returns. The authors argue that differences in performance persistence across market conditions may be explained by time-varying differences in the participation of unsophisticated investors in the mutual fund market, with a higher fraction of unsophisticated investors leading to larger deviation from the no-predictability equilibrium. Consistently with this hypothesis, the authors report that time-variation in predictability is concentrated among funds catering to retail investors.

Like Berk and Tonks (2007) and Glode et al. (2011), we also attribute differences in performance persistence to investor heterogeneity in their degree of financial sophistication. However, in light of our theoretical results, we take a different view on performance persistence. While these authors hypothesize that observed performance persistence is a consequence of investors' failure to respond optimally to differences in expected performance, we show how performance persistence may instead be the consequence of true differences in equilibrium expected performance. Of course, in reality both sources of performance persistence may coexist. For instance, the difficulties of accessing information induces lower sensitivity of flows to performance, which tends to increase persistence, but the selection effect associated with less visible funds described in our model induces less cross-sectional differences in persistence and, therefore, less persistence in realized performance. From an empirical point of view, we identify a new source of cross-sectional differences in performance persistence, i.e., fund visibility. In sum, we view the theoretical and empirical results of our paper as complementary to those of Berk and Tonks (2007) and Glode et al. (2011).

The rest of the paper is organized as follows. In section 2, we present the theoretical framework of our analysis. In section 3, we describe the data set. In section 4 we present our empirical strategy and

[3]Elton et al. (2011) also regress performance on past performance, fund size, lagged flows, and other fund characteristics. While they find that lagged flows and size are associated with lower future performance, this association is much weaker than that of past performance with future performance.

the empirical results. Section 5 concludes. The Appendix contains all proofs.

2 The model

BG consider a fund that can generate returns in excess of a passive benchmark due to its manager's ability. Let R_t denote the return in excess of a passive benchmark before fees and expenses, $R_t = \alpha + \varepsilon_t$, where α reflects managerial ability and ε_t is an idiosyncratic shock that is normally distributed with mean 0 and variance σ^2. Managerial ability, α, is not known to managers or investors, who estimate it using the information contained in past returns.

The cost of managing the portfolio is denoted by $C(q)$, where q, is the dollar value of assets under management. $C(q)$ is common knowledge and it satisfies the following properties: $C(0) = 0$, $\lim_{q\to\infty} C'(q) = \infty$ and for all $q \geq 0$, $C(q) \geq 0$, $C'(q) > 0$, $C''(q) > 0$. The last assumption, increasing marginal costs, is key to the model's implications.

The fund's net return is defined as $r_t \equiv R_t - \frac{C(q_t)}{q_t} - f$, where q_t is the $t-1$ investment in the fund and f is the fund's fee. We assume that the fee is exogenously given.

We depart from BG in that we consider a fund that targets investors with different degrees of sophistication and in that investors have limited funds to invest. To model different degrees of sophistication we allow for reservation returns to vary across investors. More specifically, we assume that each investor i has a specific search cost γ_i that reflects her ability to find an alternative fund. For simplicity, we assume that the alternative for all investors is an indexed fund with 0 return. Therefore, net of search costs, the reservation return of the $i-th$ investor is $-\gamma_i$. Unlike in the model of BG, the investor's reservation return is different from zero and is also different across investors. We assume that there is a continuum of investors with absolute value of the reservation return γ uniformly distributed over the interval $\left[0, \gamma^{Sup}\right]$, with $\gamma^{Sup} \leq 1$.[4]

The timing of the events is the following:

Date $t-1$:

- Investors enter the fund. We denote by $\overline{\gamma}$ the absolute value of the reservation return of the most sophisticated investor who enters the fund, and by γ_{MAX} the fund's least sophisticated investor's reservation return in absolute value.

Date t:

- The fund's return at date t is realized and current investors obtain its net return.

[4]Therefore, we assume that all investors in the economy have negative reservation returns net of search costs. Alternatively we could allow some investors to have positive reservation returns without altering the conclusions.

- After observing the return at date t, the fund's current investors decide whether to reinvest with the fund or withdraw their current investment.

- In addition to current investors, new investors may want to invest in the fund. However, the fund has a limited pool of potential investors: all current investors plus investors with reservation returns above $-\overline{\gamma}$, so the fund's target investors at t have reservation returns in absolute value uniformly distributed over the interval $[0, \gamma_{MAX}]$. The new investors who enter the fund pay an entry cost K.

- We assume that each current investor holds an investment in the fund that is worth m dollars at t. On this date, each investor is endowed with a wealth of m dollars. However, each investor i is exposed to the possibility of a liquidity shock with probability γ_i. Consequently, the expected investment at t by investor i is $m(1-\gamma_i)$.

- If the revenues collected by the manager at t cover the fixed costs of the fund, F, the fund continues its activity, otherwise the fund closes down. We assume for simplicity that $F = 0$.

Date $t+1$:

- The fund's return at date $t+1$ is realized and the fund's investors obtain its net return.

We study equilibrium at t.

Upon observing the series of net returns and total assets under management $\{r_s, q_s\}_{s=0}^{s=t}$, investors can infer the series of returns $\{R_s\}_{s=0}^{s=t}$ and update their beliefs about the managerial ability through Bayesian updating:

$$\phi_{t+1} = E\left(R_{t+1} \left| R_1, ..., R_t \right.\right).$$

Investor i demands shares of the fund if the fund's expected net return exceeds her reservation return $-\gamma_i$. The expected performance in period t equals

$$\begin{aligned} TP_{t+1}\left(q_{t+1}\right) &= E\left[r_{t+1} | R_1, ..., R_t\right] \\ &= E\left[R_{t+1} - \frac{C\left(q_{t+1}\right)}{q_{t+1}} - f \middle| R_1, ..., R_t\right]. \end{aligned}$$

A current investor will either withdraw her date-$t-1$ investment from the fund or keep her current investment and invest her date-t endowment in the fund depending on whether the fund's expected net return at date t is below or above her reservation return. In an equilibrium at t in which only current investors enter the fund, the following conditions must hold:

- The fund's expected performance is given by $TP_{t+1}\left(q_{t+1}^*\right) = \phi_{t+1} - \dfrac{C\left(q_{t+1}^*\right)}{q_{t+1}^*} - f$, where ϕ_{t+1} denotes the fund's alpha, and q_{t+1}^* is the equilibrium amount of assets under management.

- All investors who have withdrawn their money from the fund have reservation returns higher than $TP_{t+1}\left(q^*_{t+1}\right)$.
- All investors who have invested new money in the fund have reservation returns less than or equal to $TP_{t+1}\left(q^*_{t+1}\right)$.
- The equilibrium quantity q^*_{t+1} is such that $0 \leq q^*_{t+1} \leq v_t + M$, where $v_t \equiv m\left(\gamma_{MAX} - \overline{\gamma}\right)$ is the value at t corresponding to the investment of current investors at $t-1$ and M denotes the maximum inflow possible in this period: $m\left(\gamma_{MAX} - \frac{1}{2}\gamma^2_{MAX}\right)$.

The cutoff reservation return, $-\gamma^*$, such that in equilibrium all current investors with reservation returns lower than $-\gamma^*$ reinvest with the fund and all investors with reservation returns higher than $-\gamma^*$ leave the fund can be obtained from:

$$\begin{aligned} TP_{t+1}\left(q^*_{t+1}\right) &= -\gamma^*, \\ \text{where } q^*_{t+1} &= 2m\left(\gamma_{MAX} - \gamma^*\right) - \frac{m}{2}(\gamma^2_{MAX} - \gamma^{*2}). \end{aligned}$$

Depending on the value of the solution γ^*, there are three possible alternatives:

Case 1: $\gamma_{MAX} \leq \gamma^*$. All current investors exit the fund and therefore, $q^*_{t+1} = 0$. In this case the fund closes down.

Case 2: $\overline{\gamma} \leq \gamma^* < \gamma_{MAX}$. There is simultaneous exit and re-entry of current investors. Current investors with high reservation return exit and those with low reservation return invest also their period $t's$ endowment. The expected net return in this case is $E\left(r_{t+1}\right) = -\gamma^* < 0$.

Case 3: $\gamma^* < \overline{\gamma}$. There is re-entry of all current investors and possible entry of new investors, $q^*_{t+1} > 2m\left(\gamma_{MAX} - \gamma^*\right) - \frac{m}{2}(\gamma^2_{MAX} - \gamma^{*2})$. In this case, we are interested in whether new investors would pay the cost K to enter the fund. In an equilibrium in which new investors enter the fund the following conditions must hold:

- The fund's expected return equals $TP_{t+1}\left(q^{**}_{t+1}\right)$.
- New investors who invest in the fund have reservation returns less than or equal to $TP_{t+1}\left(q^{**}_{t+1}\right) - K$.
- New investors who decide not to invest in the fund have reservation returns higher than $TP_{t+1}\left(q^{**}_{t+1}\right) - K$.

The cutoff reservation return, i.e., the reservation return of the most sophisticated investor who enters the fund, which we denote by $-\gamma^{**}$, is obtained from:

$$\begin{aligned} TP_{t+1}\left(q_{t+1}^{**}\right) - K &= -\gamma^{**}, \\ \text{where } q_{t+1}^{**} &= v_t + m\left((\gamma_{MAX} - \gamma^{**}) - \frac{1}{2}(\gamma_{MAX}^2 - (\gamma^{**})^2)\right). \end{aligned}$$

We now distinguish two cases depending on whether the solution γ^{**} is higher or smaller than $\overline{\gamma}$. When $\gamma^{**} \geq \overline{\gamma}$, no new investors want to enter the fund because the performance of the fund is lower than the sum of their reservation return and the entry cost. As a result, the amount invested in the fund at $t+1$ equals $2v_t - \frac{m}{2}(\gamma_{MAX}^2 - \overline{\gamma}^2) \equiv \overline{q}_{t+1}$ and the expected return in this case is $E\left(r_{t+1}\right) = TP_{t+1}\left(\overline{q}_{t+1}\right)$.

On the other hand, when $\gamma^{**} < \overline{\gamma}$, new investors want to enter the fund. The last investor i to enter the fund in the period t will have $\gamma_i = \gamma^{**}$, and the quantity invested in the fund is $q_{t+1}^{**} = v_t + m\left((\gamma_{MAX} - \gamma^{**}) - \frac{1}{2}(\gamma_{MAX}^2 - (\gamma^{**})^2)\right)$. If the equation above has a negative solution, then potential investors enter the fund so the fund' most sophisticated investor reservation return is zero and the quantity invested in the fund is $v_t + m\gamma_{MAX}\left(1 - \dfrac{\gamma_{MAX}}{2}\right) = v_t + M$. Consequently, the fund's expected net return is $E\left(r_{t+1}\right) = K - \gamma^{**}$, if $\overline{\gamma} > \gamma^{**} > 0$ and $E\left(r_{t+1}\right) = TP_{t+1}\left(v_t + M\right)$, if $\gamma^{**} \leq 0$.

Let us assume for simplicity that $C\left(q\right) = cq^2/2$.

Proposition 1 *The expected net return of a fund that targets investors in the interval* $[0, \gamma_{MAX}]$ *equals*

$$E\left(r_{t+1}\left(\phi_{t+1}\right)\right) = \begin{cases} -\gamma^{*}, & if \quad \Phi_1 \leq \phi_{t+1} < \Phi_2 \\ TP_{t+1}\left(\overline{q}_{t+1}\right), & if \quad \Phi_2 \leq \phi_{t+1} < \Phi_2 + K \\ K - \gamma^{**}, & if \quad \Phi_2 + K \leq \phi_{t+1} < \Phi_3 + K \\ TP_{t+1}\left(v_t + M\right), & if \quad \Phi_3 + K \leq \phi_{t+1}, \end{cases}$$

where Φ_j, $j = \overline{1,3}$ *are defined in the Appendix and* γ^{*}, γ^{**}, *equal:*

$$\begin{aligned} \gamma^{*} &= \frac{1}{cm}\left(1 + 2cm - A^{1/2}\right), \ where \\ A &\equiv 1 + 2cm\left(2 + \phi - f\right) + c^2m^2\left(2 - \gamma_{MAX}\right)^2 \end{aligned}$$

and

$$\begin{aligned} \gamma^{**} &= \frac{1}{cm}\left(1 + cm - B^{1/2}\right), \ where \\ B &\equiv 1 + 2cm\left(1 + \phi - f - K\right) + c^2m^2\left(\left(1 - \gamma_{MAX}\right)^2 - \frac{2}{m}v_t\right), \end{aligned}$$

respectively.

Proposition 1 shows that the fund's expected net return in equilibrium can be different from 0, in contrast to BG. On the one hand, equilibrium expected net returns may be negative in our setup when investors prefer to keep their investment in the fund despite earning a negative return because this return is still higher than their reservation return. On the other hand, positive equilibrium expected net returns can be obtained when managerial skill increases and entry costs prevent new investors from entering the fund and eroding funds' performance. Therefore, the interaction of entry costs, financial constraints and negative reservation returns prevents investors' money flowing freely into and out of the fund and eliminating differential performance.

As we can see from Proposition 1, expected net return of a given fund depends on the fund's target of investors, given by γ_{MAX}. Notice that both γ^{*} and γ^{**} increase with γ_{MAX} and this is due to the fact that when the target investors are more sophisticated, there is a larger amount available for reinvestment in the fund, and therefore, the fund performance is eroded to a larger extent by money inflows. As a result, if the fund targets more sophisticated investors it may earn a higher expected net return in equilibrium. However, this does not guarantee that funds that target more sophisticated investors always outperform the funds that target less sophisticated investors. To see this, let us consider two funds: a more visible fund, which targets unsophisticated investors $\left(\gamma_{MAX}^{U}\right)$, and a less visible fund, whose potential investors are more sophisticated $\left(\gamma_{MAX}^{S}\right)$, with $\gamma_{MAX}^{U} > \gamma_{MAX}^{S}$. We assume that the total amount currently invested in the two funds is the same, v_t. We denote by Φ_j^U, Φ_j^S the cut-off points for the returns for the fund that target unsophisticated and sophisticated investors, respectively.

Proposition 2 *There exist K_1 and K_2 as defined in the Appendix such that:*

1. If $K < K_1$, then $E^S\left(r_{t+1}\left(\phi_{t+1}\right)\right) > E^U\left(r_{t+1}\left(\phi_{t+1}\right)\right)$.

2. If $K \in [K_1, K_2]$ then there exist $\phi_1 \in \left(\Phi_2^U, \Phi_2^U + K\right)$ and $\phi_2 \in \left(\Phi_2^S, \Phi_2^S + K\right), \phi_2 > \Phi_2^U + K$ such that $E^S\left(r_{t+1}\left(\phi_j\right)\right) = E^U\left(r_{t+1}\left(\phi_j\right)\right),\ j = 1, 2$. Then, for any $\phi_{t+1} < \phi_1$ and $\phi_{t+1} > \phi_2$, we have that $E^S\left(r_{t+1}\left(\phi_{t+1}\right)\right) > E^U\left(r_{t+1}\left(\phi_{t+1}\right)\right)$ and for $\phi_{t+1} \in \left(\phi_1, \phi_2\right)$, $E^S\left(r_{t+1}\left(\phi_{t+1}\right)\right) > E^U\left(r_{t+1}\left(\phi_{t+1}\right)\right)$.

3. If $K > K_2$, then there exists $\phi_1 \in \left(\Phi_2^U, \Phi_2^U + K\right)$ such that $E^S\left(r_{t+1}\left(\phi_1\right)\right) = E^U\left(r_{t+1}\left(\phi_1\right)\right)$. Then, for any $\phi_{t+1} < \phi_1$, $E^S\left(r_{t+1}\left(\phi_{t+1}\right)\right) > E^U\left(r_{t+1}\left(\phi_{t+1}\right)\right)$ and for $\phi_{t+1} > \phi_1$, $E^S\left(r_{t+1}\left(\phi_{t+1}\right)\right) < E^U\left(r_{t+1}\left(\phi_{t+1}\right)\right)$.

Proposition 2 characterizes when the fund that targets more sophisticated investors outperforms the fund that targets unsophisticated investors. Our model implies that, holding managerial skill constant, we should observe more funds sold to unsophisticated investors among poorly performing funds. Therefore, funds purchased by sophisticated investors with poor past performance are more likely to have experienced bad luck than underperforming funds targeted to unsophisticated investors. Since performance due to bad lack reverts to the mean, we should expect less persistence in fund underperformance for those funds

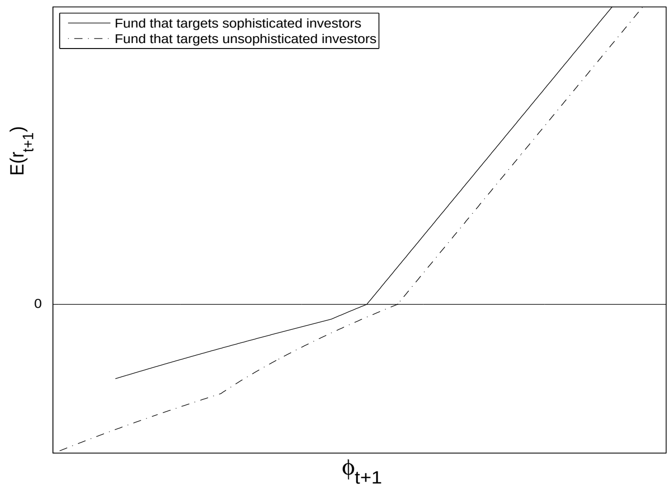

Figure 2: Expected net return for funds that target sophisticated vs. non-sophisticated investors. Case $K < K_1$

whose investor base consists of more sophisticated investors. The model is more ambiguous about which type of fund is more likely to outperform and therefore, we have no clear prediction about whether good performance should be more or less persistent for either type of fund.

When entry costs are small, $K < K_1$ (see Figure 2 for the case $K = 0$), a fund that targets more sophisticated investors outperforms for any level of managerial skill a fund that targets more unsophisticated investors. When entry costs are low enough, for any given of managerial skill a fund that is visible to the least sophisticated investors captures more investors, which reduces its performance. As can be seen in Figure 2, the performance gap between funds targeted to sophisticated investors and funds targeted to unsophisticated investors narrows as managerial skill increases. This is because it takes a low level of managerial skill for all current investors of the latter to decide to reinvest with the fund: They have lower reservation returns and, because they have less money to invest, their decision to reinvest is not as harmful for fund performance. Once all current investors have decided to reinvest, new investors enter the fund but entry of new investors has a less detrimental effect on fund performance than reinvestment by current investors. Therefore, for low entry costs, differences in expected performance between both funds are more apparent in the lower end of managerial skill.

Figure 3 shows the expected performance of both types of funds when $K \in [K_1, K_2]$. In this case, there exists an interval, (ϕ_1, ϕ_2) in which the fund targeted to unsophisticated investors outperforms the fund targeted to sophisticated investors. When all current investors have decided to reinvest in the fund targeted to unsophisticated investors, no new investors are willing to enter the fund as long as its expected

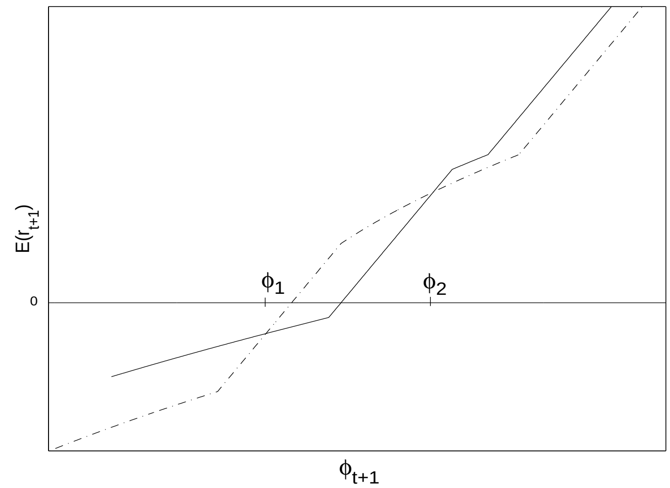

Figure 3: Expected net return for funds that target sophisticated vs. non-sophisticated investors. Case $K \in [K_1, K_2]$

performance does not exceed the reservation return of the least sophisticated new investor plus the entry cost. In that interval, the fund's expected performance increases one-to-one with managerial skill. The fund targeted to sophisticated investors, however, continues to retain its current investors' investment and attract their $t-$date endowment, so its expected performance increases slowly with skill. The lower bound of the entry cost interval, K_1, guarantees that the expected performance of both types funds cross in the interval $\left(\Phi_2^U, \Phi_2^U + K\right)$. Existence of the intersection is guaranteed by the fact that unsophisticated investors have less money to invest, which gives them a performance advantage over funds targeted to sophisticated investors when current investors have reinvested with both funds and no new investors have decided to enter. For high levels of skill, new investors start to enter the fund. Since new investors in the fund targeted to less sophisticated investors enter for lower levels of skill (because they are not so sophisticated), its expected performance deteriorates sooner as skill improves. In the limit, all possible investors decide to invest. Since the fund targeted to less sophisticated investors attracts a larger set of investors, it is larger and must necessarily underperform.

Finally, when entry costs are very high, i.e., when $K > K_2$, there will be no new investors willing to enter the fund for a the range of managerial skill considered (see Figure 4). In this case, the fund that targets unsophisticated investors outperforms the fund that targets more sophisticated investors for levels of expected managerial skill that are above a minimum level, ϕ_1.

Our model predicts that both negative and positive expected performance are possible in equilibrium in a market with frictions. It also shows that funds that more visible funds will exhibit lower expected

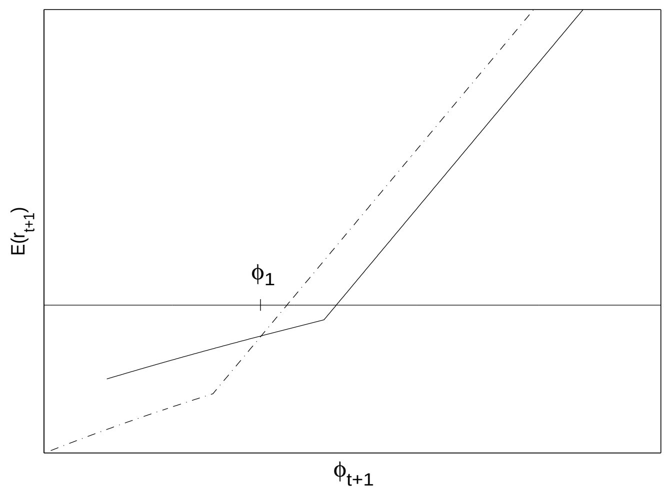

Figure 4: Expected net return for funds that target sophisticated vs. non-sophisticated investors. Case $K > K_2$

performance for low levels of managerial skill. However, more visible funds may outperform funds targeted to more sophisticated investors, as long as unsophisticated investors are more financially constrained and entry costs for new investors are sufficiently high.

3 Data

Our main source of data is the CRSP Survivor-Bias-Free US Mutual Fund Database. Since some of the variables employed in the analysis are available only since the early 1990s, we restrict our attention to the 1993-2010 period. We exclude index, non-domestic, non-diversified, and non-equity funds.[5] We aggregate monthly data for different share classes at the fund level. In particular, we compute fund total net assets as the sum of assets of all share classes of the same portfolio, fund age as the number of years since inception of the oldest class, and all other variables (return, expense ratio, 12b-1 fee, front-end and back-end loads) as asset-weighted averages of those variables at the class level. We also compute family age and family assets as the age of the oldest fund in the family and the sum of assets of all funds in the

[5]To identify US domestic equity funds, we use the information in CRSP on investment category as follows. For years in which the only objective code available is Wiesenberger's (wbrger_obj_cd), we consider as US domestic equity those funds with the codes: G; G-I; I-G; MCG; GCI; LTG; MCG; SCG; and IEQ. For years 1993-1999, we use the si_obj_cd codes: AGG; GMC; GRI; GRO; ING; SCG. For years 2000-2010, we use the lipper_class_name codes: LCVE; MLVE; EI; EIEI; LCCE; MLCE; LCGE; MLGE; MCVE; MCCE; MCGE; SCVE; SCCE; and SCGE. Index funds are identified by the CRSP's index_fund_flag variable when available and by portfolio name otherwise.

family, respectively. Funds and families are identified using CRSP's crsp_portno and mgmt_cd variables, respectively. When those variables are not available, we use fund name and management company name, instead. To mitigate the effect of documented biases in the CRSP database, we exclude all fund-month observations with total net assets below \$15 million and age less than three years (Elton et al., 2011; Evans, 2010). We winsorize fee and return data at 1% of each tail each month.

Throughout the paper, we evaluate mutual fund performance using Carhart's (1997) four-factor model:

$$r_{it} = \alpha_i + \beta_{rm,i} rm_t + \beta_{smb,i} smb_t + \beta_{hml,i} hml_t + \beta_{pr1y,i} pr1y_t + \varepsilon_{it}, \tag{1}$$

where r_{it} is fund i's return in month t in excess of the 30-day risk-free interest rate, as proxied by Ibbotson's one-month Treasury bill rate, and rm_t, smb_t and hml_t denote the return on portfolios that proxy for the market, size, and book-to-market risk factors, respectively. The term $pr1y_t$ is the return difference between stocks with high and low returns in the previous year and is included to account for passive momentum strategies. We obtain the time series of interest rates, the Fama-French factors and momentum from Kenneth French's website.

To estimate fund i's risk-adjusted performance in month t, we first regress the fund's excess return on the three Fama-French factors and momentum over the previous three years. If less than 36 monthly observations of previous data are available, we require at least 30 observations. We then compute an estimate of fund i's alpha in month t, $\hat{\alpha}_{it}$, as the difference between the fund's excess return in month t and the dot product of the vectors of estimated betas and factor realizations in that month.

We are interested in testing whether past performance predicts future performance over multi-period horizons. To compute risk-adjusted performance over the prior k months in month t, which we denote by $\hat{\alpha}_{i,t-k:t-1}$, we sum monthly estimated alphas from months $t-k$ to month $t-1$. Future performance, denoted by $\hat{\alpha}_{i,t:t+m}$, is computed as the sum of monthly alphas from months t to month $t+m$. Throughout the paper, we will focus on annual performance, so we set $k = 12$ and $m = 11$.

We compute flows of money to mutual funds from monthly data on assets under management and returns. In particular, monthly dollar flows in month t are computed as $TNA_t - TNA_{t-1}(1 + r_t)$, where TNA and r denote the fund's total net assets and net return, respectively. Once we have computed monthly dollar flows, we compute annual flows by adding dollar flows over the year. In our regressions, we use annual relative flows defined as total annual flows divided by total net assets at the end of the previous year.

The final dataset contains information on an average number of 1,251 funds and 327 fund families per month. Panels A and B of Table I contain summary statistics of fund characteristics and performance for the 1993-2000 and 2001-2010 sample periods, respectively.

We use the following proxies for fund visibility:

1. Number of different investment categories in which the family offers mutual funds;

2. Family size, as proxied by the natural logarithm of total family assets;

3. Family age, computed as the age of the oldest fund in the family.

These variables have been previously proposed by Huang et al. (2007) as proxies for investor participation costs. Low values of these variables characterize less visible and, therefore, hard-to-find funds. We assume that, because of the higher cost of locating these funds, potential investors include only those who enjoy low search costs due to their higher level of education, financial literacy, intelligence, or access to unbiased advice. We decide to focus on family-level variables for two reasons. First, strategic decisions such as distribution and advertising are taken at the fund family level. As pointed out by Gallaher et al. (2006), "decisions such as advertising budget, what and when to advertise, the types and number of funds to offer, which distribution channels to pursue, service quality, or individual manager appointments primarily originate on the mutual fund family level." Second, evidence on spillover effects within families (Nanda et al., 2004) suggests that funds in the same family may share the same set of potential investors.

For each one of these proxies, we create two dummy variables, denoted by LO and HI, which equal one if fund i belongs to the bottom and top quartiles of the variable's distribution in data the month prior to the evaluation period, respectively.

While sophisticated investors use reliable sources of information, such as analysts' recommendations or their own research, to assess mutual fund performance, it is plausible to think that unsophisticated investors rely more on advertising. Therefore, in addition to the three variables on fund visibility described above, we also use advertising as a proxy for the degree of sophistication of a fund's target investors. More specifically, we obtain data on advertising expenditures at the family level from Kantar Media, which tracks advertising activity in a large variety of media including magazines, newspapers, television, internet, and radio. We are able to collect information on family advertising for about 18% of all fund-month observations in the 1995-2009 period. For each family and month, we compute the average advertising expenditure over the previous 12 months. For this variable, we define the HI subsample as that containing funds the top quartile of the month's distribution. It should be noted, however, that this subsample only has 822 fund-month observations, so results for this subsample should be taken with caution. We set LO equal to one if the fund's family is not contained in the advertising database for that month.

Table 2 compares funds in the LO and HI subsamples on the basis of selected fund characteristics. Less visible funds according to the number of investment categories, family size and family age, are substantially smaller; they charge lower front-end loads, 12b-1 fees, and back-end loads, but higher management fees; and they exhibit better risk-adjusted performance although the difference in performance is not statistically significant. Overall, these characteristics can be regarded as consistent with the idea that funds in less visible families are associated with lower marketing fees and have a more restricted investor base. When we use family advertising to proxy for fund visibility, we still find that funds in the *LO* subsample are smaller and charge higher management fees. However, these funds also charge higher back-end loads and exhibit worse performance.

4 Empirical strategy and results

4.1 Methodology

To estimate persistence in mutual fund performance, the literature has employed two main alternative methodologies. The more traditional approach consists of sorting funds at the beginning of each evaluation period on the basis of their past performance. Funds are then grouped in quantile portfolios and portfolio returns are computed over the evaluation period. Finally, risk-adjusted performance is measured using the time series of portfolio returns. Failure to find differences in risk-adjusted performance across portfolios is interpreted as lack of persistence in mutual fund performance. This approach has been employed to study performance persistence by Hendricks et al. (1993), Gruber (1996) and Carhart (1997), and Elton et al. (2011), among others. The portfolio-based approach serves two purposes: It tests for persistence in performance and it quantifies the value of investing on the basis of past performance. However, the approach suffers from the same problem as all nonparametric methods, i.e., it requires a large amount of data in multivariate settings. Suppose we wished to test for performance persistence while controlling for the effect of fund size on future performance. We could sort funds on both past performance and size, allocate funds to the resulting performance-size bins, and then compare portfolios that are neutral to size but correspond to different quantiles of past performance. Also, if our goal were to test whether performance persistence changes with size, we could compare portfolios across both past performance and size bins. In both cases, the number of bins grows geometrically with the number of fund characteristics whose effect on performance we wish to measure.

As an alternative, the regression-based approach consists of regressing future performance on past performance and then testing whether the regression coefficient is zero. This approach has been used by Busse et al. (2010), Elton et al. (2011) and Ferreira et al. (2010). By imposing a parametric specification on the functional relation between future performance and past performance and other variables, we can control for the effect of fund characteristics on performance and allow for persistence to vary with those characteristics with less stringent data requirements.

Because we are interested in testing whether the degree of performance persistence changes with fund visibility while controlling for a number of other variables, we choose the regression approach. We start by regressing future performance on past performance. Then, we allow for possible non-linearities and regress future performance on dummy variables corresponding to different deciles of past performance.

4.2 Fund visibility and performance persistence

To evaluate the prevalence of performance persistence in the entire sample, we estimate by pooled OLS the regression equation:

$$\hat{\alpha}_{i,t:t+11} = \delta_{0,t} + \delta_1 \hat{\alpha}_{i,t-12:t-1} + \Delta X'_{i,t-1} + \varepsilon_{i,t:t+11}, \tag{2}$$

where each observation corresponds to one fund-month pair, X is a row vector of control variables, and ε denotes a generic error term. Control variables include: fund size in month $t-1$, defined as the natural logarithm of the fund's assets; relative flows of money into the fund during the year ending in month $t-1$; fund age, defined as the natural logarithm of the fund's age in months; family size in month $t-1$, defined as the natural logarithm of the assets under management of the management company to which the fund belongs; and family age, defined as the natural logarithm of the management company's age in months. We also control for the fund's maximum front-end load, maximum back-end load, expense-ratio, and turnover ratio. Since values of fees and turnover are reported for the entire fiscal year, their value in month $t-1$ is not strictly lagged with respect to future performance unless month $t-1$ is the last month of the fiscal year. To ensure that those variables are known before month t, we use a lag of 12 months for them. We include monthly dummies in the regression and compute standard errors clustered by both fund and month to correct for serial and cross-sectional correlation of residuals, respectively.

The first column in Table 3 reports estimation results for equation (2). The coefficient on past performance is positive and statistically significant at the 1% confidence level, which suggests that past performance persists for periods of at least one year, consistently with previous studies. Both fund size and lagged flows are negatively and significantly associated with performance, consistent with BG's diseconomies of scale hypothesis. Funds belonging to larger management companies are associated with better performance, as documented by Chen et al. (2004). Finally, the fund's back-end load, expense ratio and turnover ratio are negatively related to performance, although the coefficient for turnover ratio is only marginally statistically significant. In sum, these results are consistent with a large body of empirical evidence that future US equity fund performance is predictable from the cross-section of past performance and other fund characteristics.

We then interact the dummy variables LO and HI obtained according to the four proxies of fund visibility with past performance and estimate the regression equation:

$$\hat{\alpha}_{i,t:t+11} = \theta_{0,t} + \theta_1 \hat{\alpha}_{i,t-12:t-1} + \theta_2 \hat{\alpha}_{i,t-12:t-1} LO_{i,t-1} + \theta_3 \hat{\alpha}_{i,t-12:t-1} HI_{i,t-1} + \\ + \theta_4 LO_{i,t-1} + \theta_5 HI_{i,t-1} + \Theta X'_{i,t-1} + \varepsilon_{i,t:t+11}, \quad (3)$$

where we also include the two dummy variables to allow for the possibility of different means for each group of funds. We are mainly interested in the coefficients θ_2 and θ_3. Columns 2-5 of Table 3 show the estimation results for each of the four proxies. The coefficients of the interaction of performance with the *LO* dummy (θ_2) are negative in all four cases and statistically significant at the 1% level (family age), 5% level (number of investment categories and family advertising), and 10% level (family size). Estimation results, therefore, suggest that differences in performance are shorter-lived for the least visible funds than for the rest of funds. Moreover, in contrast to other funds, less visible funds exhibit no performance persistence: The regression coefficient on past performance for these funds, $\theta_1 + \theta_4$, is not statistically significant for any of the proxies (unreported). However, we do not find differences in performance persistence between highly visible funds and the rest of funds, which suggests that the relation between visibility and persistence is non-monotonic.

An obvious concern about these results is the possibility that our proxies for visibility capture differences in persistence across funds due to other fund characteristics. As mentioned in the introduction, Elton et al. (2011) test the hypothesis that there should be less performance persistence among larger funds, for which diseconomies of scale are more likely to be important, although they do not find support for that hypothesis. Also, funds in different investment categories may exhibit different degrees of performance persistence due to differences in the nature of the markets in which they operate. To control for both possibilities, we include interactions of performance with fund size and with dummies for investment categories. The estimation results are reported in Table 4. The coefficients on the interactions of size with performance are negative, but not statistically significant except in column 3 (Family Size), where it is only marginally significant. The fact that the interaction of performance with size is not significant provides further support to the finding of Elton et al. (2011) that performance persistence does not decline with fund size. Further, all signs for the interactions of past performance with the *LO* dummies are negative and the coefficients are statistically significant at the 1% level in all cases except for the family advertising proxy (5%).

In sum, the results of Table 3 and 4 are strongly indicative that there exist differences in performance persistence associated with fund visibility and that these differences in persistence cannot be explained by differences in fund size or differences in investment categories.

4.3 Performance persistence for winners and losers

Low persistence among certain types of funds may be the consequence of either recent underperformers improving their performance or recent outperformers delivering lower performance, or both. To disentangle the reason why less visible funds exhibit less persistent differences in performance, we estimate the regression equation:

$$\begin{aligned}\hat{\alpha}_{i,t:t+11} &= \delta_{0,t} + \sum_n \delta_{1,n} dec\_n_{i,t-1} \\ &+ \sum_n \delta_{2,n} dec\_n_{i,t-1} LO_{i,t-1} + \sum_n \delta_{3,n} dec\_n_{i,t-1} HI_{i,t-1} \\ &+ \delta_4 LO_{i,t-1} + \delta_5 HI_{i,t-1} + \Delta X'_{i,t-1} + \xi_{i,t:t+11}, \qquad (4)\end{aligned}$$

where $dec\_n_{i,t-1}$ is a dummy variable that equals one if fund i's performance is in the n-th decile of all funds' alphas over the prior twelve months. We omit the dummy variables corresponding to the four central performance deciles, i.e., we only include in the regression the dummy variables corresponding to the top three and bottom three performance deciles.

Once equation 4 has been estimated, we test whether the underperformance of funds in the LO subsample is shorter-lived than that of otherwise similar recent underperformers. More specifically, $\delta_{1,1} + \delta_{2,1}$ captures the difference in expected performance between a LO-fund whose past performance belongs to the first decile of the distribution and an otherwise identical LO-fund with past performance in the central deciles. The coefficient $\delta_{1,1}$ captures the difference in expected performance between a fund outside the LO and HI subsamples whose past performance belongs to the first decile of the distribution and an otherwise identical fund with performance in the central deciles. Therefore, a positive value of $\delta_{2,1}$ implies that the performance of underperforming LO-funds converges faster to the median fund's performance than the performance of funds that do not belong to the LO or HI subsamples. Analogously, a negative value of $\delta_{2,10}$ indicates that the performance of outperperforming LO-funds converges faster to the median fund's performance than the performance of funds that do not belong to the LO or HI subsamples.

Similarly, $\delta_{3,1}$ ($\delta_{3,10}$) is positive (negative) if HI-funds in the bottom (top) performance decile converges to that of the median fund faster than that of funds with $LO = HI = 0$.

Column 1 of Table 5 reports estimation results when no interactions with LO and HI are included in the regression equation. The estimated coefficients on the three bottom (top) performance decile dummies are negative (positive) and statistically significant at any significance level. Future performance also appears to increase monotonically with past performance. Differences in performance across deciles are economically significant: Recent top performers outperform otherwise identical funds in the bottom decile by 180 basis points per year.

In columns 2-4 we report estimation results when interactions with LO and HI are included and investor sophistication is determined according to the number of investment categories in which the family offers funds, family size, and family age. The coefficient on the interaction between the bottom decile dummy and LO, $\delta_{2,1}$, is positive and statistically significant, suggesting that hard-to-find underperforming funds exhibit better relative performance than otherwise similar underperforming funds, although the coefficient is only marginally significant for family age. In contrast, none of the coefficients on the interaction of the bottom decile dummy and HI is statistically significant.

However, when we use family advertising to define fund visibility, we find no difference in performance persistence for underperforming funds in the low-visibility subsamples and otherwise similar funds. Moreover, we find that the performance of funds in families with the highest advertising expenditures reverts faster to the median fund's performance following poor recent performance. However, because of the small sample size on fund families' advertising expenditures, this result should be interpreted with caution.

We then ask whether good performance reverts faster for low-visibility funds. The answer is yes: The coefficients on the interaction terms between LO and the top decile dummy, $\delta_{2,10}$, are negative and significant for all four proxies of investor sophistication. None of the interaction terms with the top decile dummy is significant for high-visibility funds.

Therefore, the results of Table 5 suggest that the lower performance persistence documented in Tables 3 and 4 for low-visibility funds is due to these funds' performance improving faster after poor performance and, even more clearly so, to these funds' performance deteriorating faster after good performance. Good relative performance for less visible funds also lives shorter than for other funds.

4.4 Ranking on returns

So far, we have used Carhart's four-factor model to measure fund performance both in the ranking period and in the evaluation period. There is no consensus in the literature on mutual fund performance persistence as to whether the researcher should employ the same model to rank funds and measure subsequent performance. On the one hand, failing to control for a specific positively-priced risk factor in the ranking period contaminates the ranking: Top decile portfolios will contain both funds with true high alpha and funds with a high beta with respect to the omitted risk factor. On the other hand, using the same asset pricing model to sort and estimate performance will also pick up the model bias, as pointed out by Carhart (1997). While the former approach may bias results against finding persistence, the latter may bias results in favor of finding persistence.

To examine whether our conclusions are robust to ranking funds on past returns, we repeat the tests of Table 5 using fund returns measured over the last 12 months to define decile dummies. Table 6 reports the results. The estimated coefficients on the decile dummies when no interactions are included (column 1) are similar to those of Table 5 for the bottom decile dummies. However, the coefficients on the top decile dummies are much lower in absolute value than those obtained when past performance is measured using the four-factor model. In fact, there is no evidence of persistence in outperformance when funds are ranked on past returns. Therefore, funds in the top deciles of past performance are not separated from mid-ranked funds in terms of their subsequent performance.

Consistently with the results of Table 5, the underperformance of bottom-ranked funds in the low-visibility subsample tends to vanish in the subsequent year if the low-visibility subsample is defined according to the number of investment categories, family size, and family age, but not advertising expenditures. However, the coefficients on the interaction of LO with the top decile dummies are not statistically significant. Also, with one exception, none of the coefficients on the interaction of HI with the top decile dummies is statistically significant.

The results of Table 6 suggest that lack of persistence in the underperformance of the least visible funds appears to be robust to model bias. We do not find, however, that more visible funds exhibit less persistence following good performance, simply because there is no evidence of persistence in good performance when funds are ranked according to past fund returns.

4.5 Institutional investors

The prediction that differences in persistence should be associated with differences in investor sophistication could be tested in a more direct way if we could measure the degree of sophistication of a fund's investors. A natural candidate for sophisticated investors are institutional investors. Del Guercio and Tkac (2002) document that pension fund sponsors are more likely to use risk-adjusted measures of performance than mutual fund investors when evaluation professional portfolio managers. They also find that pension managers, unlike mutual fund managers, are penalized for poor performance. Both findings are consistent with the idea that pension plan sponsors are more sophisticated than mutual fund investors, most of which are retail investors. Glode et al. (2011) distinguish between retail and institutional mutual fund investors and find substantial performance persistence following good markets, but only in the retail segment of the mutual fund market.

If the differences in performance persistence between low visibility funds and the rest of funds documented in the previous section simply capture differences between retail and institutional investors, then removing institutional funds from the sample should eliminate or mitigate the results. To investigate this possibility, we estimate regression (4) excluding institutional funds. Institutional funds are defined as those containing institutional share classes only. We use the CRSP identifiers for institutional shares, when available, and the fund's or class' name otherwise. Estimation results are reported in Table 7.

Results are very similar to those of Table 5. However, the evidence that performance reverts for outperforming low-visibility funds is now weaker. In particular, the coefficients on the interaction of the top decile dummy with *LO* are not statistically significant when family age and family advertising are use to proxy for advertising.

One possible interpretations of our results is that the institutional/retail mutual fund classification does not effectively help us distinguish between unsophisticated and sophisticated investors. Consistently with this interpretation, James and Karceski (2006) find that, despite charging significantly lower management expenses, institutional funds do not outperform retail mutual funds. However, institutional funds with large minimum initial investment requirements ("large institutional funds") outperform both the retail mutual funds and other institutional funds. Flows of money to large institutional funds are also more sensititive to risk-adjusted performance than flows of money to small institutional funds. They attribute differences within the institutional segment to differences in sophistication or agency costs.

5 Conclusions

Why do differences in performance across mutual funds persist through time? While the previous literature has attributed performance persistence to investors' failure to response to differences in expected performance, in this paper, we show that the interaction of different market frictions that characterize the mutual fund market can generate cross-sectional differences in equilibrium expected performance.

Although frictions are generally not observable, in our empirical tests we exploit the model's prediction that hard-to-find funds should exhibit less dispersion in expected performance and, therefore, less persistence in observed performance differences. Consistently with this prediction, our test results suggest that less visible funds and funds in families that advertise less, exhibit a substantially lower degree of persistence in performance. Moreoever, persistence of past underperformance appears to be robust to model bias. However, we do not find that differences in persistence are associated with institutional fund ownership.

The results of the paper highlight the prevalence of limits to arbitrage in retail financial markets. Previous studies have noted that price competition alone may not be sufficient to eliminate differences in net performance across funds when investors fail to react to differences in expected performance and management companies react strategically (Christoffersen and Musto, 2002; Gil-Bazo and Ruiz-Verdú, 2008; Gil-Bazo and Ruiz-Verdú, 2009). In this paper, we show that even if investors react rationally to differences in expected performance, market frictions distort their choices with respect to what would be expected in a friction-less market, such as the one described by (Berk and Green 2004), and can generate predictability in fund performance.

An important implication of our results is that policies aimed at improving the efficiency of the market for mutual funds should focus on eliminating frictions and, particularly, facilitating comparisons product comparisons both within and across asset classes. The fact that funds that are easy to find exhibit a larger degree of persistence in underperformance than the hard-to-find funds suggests that a simple increase in the amount of information available to investors through mandatory disclosures may not be an effective means of improving the efficiency of this market.

6 Appendix

Proof of Proposition 1. The current investors exit or reinvest their wealth depending on whether their reservation return is lower or higher than $-\gamma^*$, where γ^* is such that $TP_{t+1}\left(q^*_{t+1}\right) = -\gamma^*$. The quantity invested in the fund is

$$q^*_{t+1} = m\left(\gamma_{MAX} - \gamma^*\right) + m\left(\left(\gamma_{MAX} - \gamma^*\right) - \frac{1}{2}(\gamma^2_{MAX} - \gamma^{*2})\right),$$

where the first term corresponds to the period $t-1$ investment that is reinvested and the second term corresponds to the period t investment. The equilibrium condition $TP_{t+1}\left(q^*_{t+1}\right) = -\gamma^*$ can be rewritten as

$$\phi - cm\left(2(\gamma_{MAX} - \gamma^*) - \frac{1}{2}(\gamma^2_{MAX} - \gamma^{*2})\right) - f = -\gamma^*. \tag{5}$$

Solving for γ^*, we obtain

$$\begin{aligned} \gamma^* &= \frac{1}{cm}\left(1 + 2cm - A^{1/2}\right), \text{ where} \\ A &\equiv 1 + 2cm\left(2 + \phi - f\right) + c^2m^2\left(2 - \gamma_{MAX}\right)^2. \end{aligned}$$

γ^* is a real solution of equation (5) if $A > 0$ and a sufficient condition for $A > 0$ is $2 + \phi > f$, which is a reasonable assumption.

Notice that if $\gamma^* < \overline{\gamma}$ all current investors re-entry and we have also possible entry of new investors. The new investors have to pay the cost K to enter the fund and therefore, their cutoff reservation return, $-\gamma^{**}$, is obtained from:

$$\begin{aligned} TP_{t+1}\left(q^{**}_{t+1}\right) - K &= -\gamma^{**}, \\ \text{where } q^{**}_{t+1} &= v_t + m\left(\left(\gamma_{MAX} - \gamma^{**}\right) - \frac{1}{2}(\gamma^2_{MAX} - \gamma^{**2})\right). \end{aligned}$$

We solve for γ^{**} from the equilibrium condition

$$\phi - cm\left(2\gamma_{MAX} - \gamma^{**} - \overline{\gamma} - \frac{1}{2}\left(\gamma^2_{MAX} - \gamma^{**2}\right)\right) - f - K = -\gamma^{**}, \tag{6}$$

and obtain

$$\begin{aligned} \gamma^{**} &= \frac{1}{cm}\left(1 + cm - B^{1/2}\right), \text{ where} \\ B &\equiv 1 + 2cm\left(1 + \phi - f - K\right) + c^2m^2\left(1 + 2\overline{\gamma} + \gamma^2_{MAX} - 4\gamma_{MAX}\right) \\ &= 1 + 2cm\left(1 + \phi - f - K\right) + c^2m^2\left(\left(1 - \gamma_{MAX}\right)^2 - \frac{2}{m}v_t\right). \end{aligned}$$

γ^{**} is a real solution of equation (6) if $B \geq 0$. For B to be higher or equal than 0 we need to have $K < \overline{K}(\gamma_{MAX}) \equiv \frac{1}{2cm}\left(1 + 2cm(1+\phi - f) + c^2m^2\left((1-\gamma_{MAX})^2 - \frac{2}{m}v_t\right)\right)$. So if $K < \overline{K}(\gamma_{MAX})$ there is a solution to equation (6), otherwise there is no real solution (and therefore no new investors enter the fund). When there is a real solution, we distinguish two cases depending on whether the solution γ^{**} is higher or smaller than $\overline{\gamma}$. When $\gamma^{**} \geq \overline{\gamma}$, no new investors want to enter the fund because the performance of the fund is lower than the sum of their reservation return and the entry cost. The expected return in this case equals $TP_{t+1}(\overline{q}_{t+1}) > -\overline{\gamma}$. On the other hand, when $0 \leq \gamma^{**} < \overline{\gamma}$, new investors enter the fund. Since the last new investor that entered has reservation return $-\gamma^{**}$, the expected return in this case is $K - \gamma^{**}$.

Notice also that both γ^* and γ^{**} increase with γ_{MAX} if $\gamma_{MAX} < 2$.

Consequently, the amount invested in the fund at time $t+1$ is

$$q_{t+1} = \begin{cases} 0, & if \quad \phi_{t+1} < \Phi_1 \\ m\left(2(\gamma_{MAX} - \gamma^*) - \frac{1}{2}(\gamma_{MAX}^2 - \gamma^{*2})\right), & if \quad \Phi_1 \leq \phi_{t+1} < \Phi_2 \\ 2v_t - \frac{m}{2}(\gamma_{MAX}^2 - \overline{\gamma}^2), & if \quad \Phi_2 \leq \phi_{t+1} < \Phi_2 + K \\ v_t + m\left((\gamma_{MAX} - \gamma^{**}) - \frac{1}{2}(\gamma_{MAX}^2 - \gamma^{**2})\right), & if \quad \Phi_2 + K \leq \phi_{t+1} < \Phi_3 + K \\ v_t + M, & if \quad \Phi_3 + K \leq \phi_{t+1}, \end{cases}$$

where $\Phi_1 \equiv f - \gamma_{MAX}$, $\Phi_2 \equiv f + 2cv_t - \overline{\gamma} - \frac{1}{2}cm\left(\gamma_{MAX}^2 - \overline{\gamma}^2\right)$ and $\Phi_3 \equiv f + cv_t + cm\gamma_{MAX}\left(1 - \frac{\gamma_{MAX}}{2}\right)$. Notice that if $\phi_{t+1} < \Phi_1$, the fund closes down. As a result the expected return equals to

$$E(r_{t+1}(\phi_{t+1})) = \begin{cases} -\gamma^* & if \quad \Phi_1 \leq \phi_{t+1} < \Phi_2 \\ TP_{t+1}(\overline{q}_{t+1}) & if \quad \Phi_2 \leq \phi_{t+1} < \Phi_2 + K \\ K - \gamma^{**} & if \quad \Phi_2 + K \leq \phi_{t+1} < \Phi_3 + K \\ TP_{t+1}(v_t + M) & if \quad \Phi_3 + K \leq \phi_{t+1}. \end{cases}$$

■

Proof of Proposition 2. Notice that, since $\gamma_{MAX}^U - \gamma_{MAX}^S > 0$, we have that $\Phi_1^S > \Phi_1^U$, $\Phi_2^S > \Phi_2^U$ but $\Phi_3^S < \Phi_3^U$.

We search for $\phi_1 \in \left(\Phi_2^U, \Phi_2^U + K\right)$ such that

$$\begin{aligned} E^S(r_{t+1}) &= E^U(r_{t+1}) \\ i.e. - \gamma^* &= \phi_1 - cq_{t+1}^* - f. \end{aligned}$$

Notice that $\phi_1 - cq_{t+1}^* - f = \phi_1 - \Phi_2^U + \Phi_2^U - cv_t - f = \phi_1 - \Phi_2^U - \overline{\gamma}^U$, and $-\gamma^* = -\left(1 + 2a - A^{1/2}\right)$. We define a by $a \equiv cm$.

Solving for A we obtain $A = \left(2a + a\left(\phi_1 - \Phi_2^U - \overline{\gamma}^U\right) + 1\right)^2$, if $2a + a\left(\phi_1 - \Phi_2^U - \overline{\gamma}^U\right) + 1 > 0$ i.e. $\phi_1 > \Phi_2^U + \overline{\gamma}^U - 2 + \frac{1}{a}$ and this is satisfied for $\phi_1 > \Phi_2^U$. Since on the other hand $A = 1 + 2a\left(2 + \phi_1 - f\right) + a^2\left(2 - \gamma_{MAX}^S\right)^2$ we have that

$$
\begin{aligned}
\left(2a + a\left(\phi_1 - \Phi_2^U - \overline{\gamma}^U\right) + 1\right)^2 &= 1 + 2a\left(2 + \phi_1 - f\right) + a^2\left(2 - \gamma_{MAX}^S\right)^2 \\
\left(2a + a\left(\phi_1 - \Phi_2^U - K - \overline{\gamma}^U + K\right) + 1\right)^2 &= 1 + 2a\left(2 + \phi_1 - \left(\Phi_2^U + K\right) + \Phi_2^U + K - f\right) \\
&\quad + a^2\left(2 - \gamma_{MAX}^S\right)^2 \\
\left(2a + a\left(-x - \overline{\gamma}^U + K\right) + 1\right)^2 &= 1 + 2a\left(2 - x + \Phi_2^U + K - f\right) + a^2\left(2 - \gamma_{MAX}^S\right)^2,
\end{aligned}
$$

where by definition $x \equiv \Phi_2^U + K - \phi_1$.

We define

$$
\begin{aligned}
T &\equiv a^2\left(2 - \gamma_{MAX}^S\right)^2 \ \textit{and} \\
\text{and } V &\equiv a\left(4cv_t - \overline{\gamma}^U - cv_t\left(\gamma_{MAX}^U + \overline{\gamma}^U\right)\right) \\
&= av_t\left(4c + \frac{1}{m} + \frac{cv_t}{m}\right) - \gamma_{MAX}^U\left(1 + 2cv_t\right).
\end{aligned}
$$

We obtain two solutions $x_{1,2}^* = \left(2 - \overline{\gamma}^U + K \pm \frac{1}{a}\sqrt{T + V}\right)$. If $\gamma_{MAX}^U < 2$ and $K > K_1 \equiv \frac{1}{a}\left(\sqrt{T + V} - a\left(2 - \overline{\gamma}^U\right)\right)$, the solution $x_1^* = \left(2 - \overline{\gamma}^U + K - \frac{1}{a}\sqrt{T + V}\right) \in (0, K)$. Consequently, $\phi_1 = \Phi_2^U + K - x_1^* \in \left(\Phi_2^U, \Phi_2^U + K\right)$.

Notice that $x_2^* = \left(2 - \overline{\gamma}^U + K + \frac{1}{a}\sqrt{T + V}\right)$ is always a positive solution but is also higher than K, so it cannot be solution of our problem.

We have shown in Proposition 1 that if $K \geq \overline{K}\left(\gamma_{MAX}^U\right) \equiv K_2$ then no new investors will enter the fund that targets the unsophisticated investors. The expected return of this fund increases one to one with ϕ_{t+1}, and since $\Phi_2^S > \Phi_2^U$ it implies that $E^U\left(r_{t+1}\left(\Phi_2^S + K\right)\right) > E^S\left(r_{t+1}\left(\Phi_2^S + K\right)\right)$ for any $\phi_{t+1} > \phi_1$.

Let us then consider the case when $K < \overline{K}\left(\gamma_{MAX}^U\right)$. To prove next that there is $\phi_2 \in \left(\Phi_2^S, \Phi_2^S + K\right)$ such that $E^S\left(r_{t+1}\right) = E^U\left(r_{t+1}\right)$ is enough to prove that $E^U\left(r_{t+1}\left(\Phi_2^U + K\right)\right) > E^S\left(r_{t+1}\left(\Phi_2^U + K\right)\right)$ and $E^U\left(r_{t+1}\left(\Phi_2^S + K\right)\right) < E^S\left(r_{t+1}\left(\Phi_2^S + K\right)\right)$.

We have shown that when $K > K_1$ it exists $\phi_1 \in \left(\Phi_2^U, \Phi_2^U + K\right)$ such that $E^S\left(r_{t+1}\right) = E^U\left(r_{t+1}\right)$ and this implies that $E^S\left(r_{t+1}\left(\Phi_2^U + K\right)\right)$ could be either $-\gamma^*$ or $\Phi_2^U + K - cq_{t+1}^* - f$. In the first case, it is straightforward that since the return does not change the slope in that interval, $E^U\left(r_{t+1}\left(\Phi_2^U + K\right)\right) >$

$E^S\left(r_{t+1}\left(\Phi_2^U+K\right)\right)$. If $E^S\left(r_{t+1}\left(\Phi_2^U+K\right)\right)=\Phi_2^U+K-cq_{t+1}^{U*}-f$ we have then that

$$\begin{aligned} E^S\left(r_{t+1}\left(\Phi_2^U+K\right)\right) &= \Phi_2^U+K-c\overline{q}_{t+1}\left(\gamma_{MAX}^U\right)-f> \\ E^S\left(r_{t+1}\left(\Phi_2^U+K\right)\right) &= \Phi_2^U+K-c\overline{q}_{t+1}\left(\gamma_{MAX}^S\right)-f\Leftrightarrow \\ q_{t+1}^*\left(\gamma_{MAX}^U\right) &< q_{t+1}^*\left(\gamma_{MAX}^S\right). \end{aligned}$$

Notice that $\overline{q}_{t+1}\left(\gamma_{MAX}\right)=2v_t-\frac{m}{2}(\gamma_{MAX}^2-\overline{\gamma}^2)=2v_t-\frac{v_t}{2}(\gamma_{MAX}+\overline{\gamma})=v_t\left(2-\frac{1}{2}(2\gamma_{MAX}-\frac{v_t}{m})\right)$. Since $\overline{q}_{t+1}\left(\gamma_{MAX}\right)$ decreases with γ_{MAX} it results that $\overline{q}_{t+1}\left(\gamma_{MAX}^U\right)<\overline{q}_{t+1}\left(\gamma_{MAX}^S\right)$.

To prove that $E^U\left(r_{t+1}\left(\Phi_2^S+K\right)\right)<E^S\left(r_{t+1}\left(\Phi_2^S+K\right)\right)$ we calculate both the expected adjusted returns evaluated in Φ_2^S+K. Notice that in this range both returns equal to $K-\gamma^{**}$ and γ^{**} increase with γ_{MAX} if $\gamma_{MAX}<1$. Since $\gamma_{MAX}^S<\gamma_{MAX}^U$ it implies $K-\gamma^{S,**}>K-\gamma^{U,**}$ and therefore $E^U\left(r_{t+1}\left(\Phi_2^S+K\right)\right)<E^S\left(r_{t+1}\left(\Phi_2^S+K\right)\right)$. If $K>\overline{K}\left(\gamma_{MAX}\right)$, the return for the sophisticated equals $E^S\left(r_{t+1}\left(\Phi_2^S+K\right)\right)=\Phi_2^S+K-c\overline{q}_{t+1}\left(\gamma_{MAX}^U\right)-f>K-\gamma^{S,**}$ and $E^U\left(r_{t+1}\left(\Phi_2^S+K\right)\right)=K-\gamma^{U,**}$, so again $E^U\left(r_{t+1}\left(\Phi_2^S+K\right)\right)<E^S\left(r_{t+1}\left(\Phi_2^S+K\right)\right)$ q.e.d. ■

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Table 1
Summary statistics.
The table shows summary statistics for the sample of US Domestic Equity mutual funds in the 1993-2010 period employed in the paper. N denotes de number of fund-month observations, except in the case of variables measured at the family level, where we only consider a single observation per family and month. $Q1$ and $Q3$ denote the 25th and 75th percentiles, respectively. Total net assets are in millions of USD. Age is the number of years since inception of the fund's oldest class. Family age is the age of the family's oldest fund. Loads, fees, turnover ratio, and returns are asset-weighted averages across all classes in the fund.

Panel A: 1993-2000

Variable	N	Mean	Std. dev.	*Q1*	Median	*Q3*
Total net assets	84287	1333.59	4040.44	93.31	278.9	921.88
Annual flow (in %)	63369	12.24	63.35	-11.43	-0.02	18.18
Age	84144	15.13	14.82	5.42	9.08	17.5
Family total net assets	26998	10981.68	40743.85	228.6	1428.47	5611.1
Family age	26987	25.86	20.68	9.67	16.25	40.5
Front-end load (in %)	37433	3.36	1.96	1.73	3.76	4.75
Back-end load (in %)	28188	1.43	1.37	0.32	1	2.17
Management fee (in %)	37991	0.74	0.24	0.6	0.75	0.9
Expense ratio (in %)	71040	1.21	0.39	0.94	1.16	1.44
12b-1 fee (in %)	22914	0.33	0.25	0.12	0.25	0.5
Turnover ratio (in %)	70452	82.28	64.63	36.2	67	109
Return (in %)	83929	15.17	66.71	-22.03	17.44	51.83
Carhart's 4-factor alpha (in %)	51181	-0.41	26.99	-13.38	-0.73	11.96

Panel A: 2001-2010

Variable	N	Mean	Std. dev.	*Q1*	Median	*Q3*
Total net assets	186114	1256.74	4946.26	80	242.7	838.8
Annual flow (in %)	145663	6.31	58.90	-15.26	-4.73	11.26
Age	185881	14.10	12.87	6.5	10.17	16.08
Family total net assets	43703	20925.18	91580.15	201.1	1265.4	7738.7
Family age	43703	28.74	21.84	12.58	20.67	38.58
Front-end load (in %)	97186	2.62	1.73	1.09	2.65	4.00
Back-end load (in %)	75535	0.76	0.89	0.10	0.43	1.09
Management fee (in %)	171168	0.72	0.25	0.59	0.75	0.89
Expense ratio (in %)	170249	1.23	0.38	0.99	1.21	1.47
12b-1 fee (in %)	127940	0.29	0.23	0.09	0.25	0.44
Turnover ratio (in %)	173993	82.15	64.48	35	66	110
Return (in %)	185859	4.56	65.30	-29.18	11.98	45.30
Carhart's 4-factor alpha (in %)	130793	-2.17	21.14	-12.01	-1.99	7.86

Table 2
Differences across visibility subsamples
The table compares selected fund characteristics across fund subsamples defined according to fund visibility. Risk-adjusted performance is estimated using Carhart's (1997) four-factor model. α denotes performance in the subsequent 12 months. Assets denotes the fund's assets under management. F-load and B-load denote the fund's asset-weighted front-end load and back-end load, respectively. 12b-1 fee and Man. fee denote the fund's 12b-1 and management fee, respectively. High denotes the subsample of funds that belong to the top quartile of the monthly distribution of: the number of investment categories in the family; family size; family age; or family advertising. Low is defined analogously for the bottom quartile, except for family advertising, in which case Low denotes subsample of funds with no reported advertising expenditures. The number of fund-year observations is reported in parentheses.

		Assets	F-load	12b-1 fee	Man. fee	α	B-load
# Inv Cat	Low	525.79	0.74%	0.12%	0.84%	-1.51%	0.12%
		(4360)	(4360)	(3675)	(3318)	(2316)	(4360)
	High	2449.55	1.63%	0.22%	0.64%	-1.66%	0.50%
		(4238)	(4238)	(3806)	(3494)	(2621)	(4238)
	Low-High	-1923.77	-0.89%	-0.10%	0.20%	0.15%	-0,38%
	S.e	88.97	0.04%	0.01%	0.01%	0.20%	0.02%
Family Size	Low	186.12	0.85%	0.14%	0.83%	-1.55%	0.16%
		(5580)	(5580)	(4709)	(4276)	(2915)	(5580)
	High	3387.16	1.71%	0.22%	0.63%	-1.73%	0.49%
		(5493)	(5493)	(4632)	(4422)	(3622)	(5493)
	Low-High	-3201.04	-0.85%	-0.08%	0.20%	0.18%	-0.33%
	S.e.	118.97	0.04%	0.00%	0.01%	0.18%	0.02%
Family Age	Low	385.02	0.69%	0.11%	0.81%	-1.63%	0.11%
		(5648)	(5648)	(4761)	(4455)	(2622)	(5648)
	High	2971.8	2.12%	0.27%	0.63%	-1.8%	0.52%
		(5619)	(5619)	(4739)	(4488)	(3692)	(5619)
	Low-High	-2586.78	-1.43%	-0.15%	0.18%	0.16%	-0.41%
	S.e.	117.58	0.03%	0.00%	0.01%	0.18%	0.01%
Family Adv.	Low	1210.00	1.38%	0.21%	0.74%	-1.91%	0.37%
		(15888)	(15888)	(14414)	(13380)	(9721)	(15888)
	High	2969.95	1.36%	0.19%	0.64%	-1.07%	0.13%
		(822)	(822)	(776)	(731)	(610)	(822)
	Low-High	-1759.95	0.02%	0.02%	0.10%	-0.84%	0.24%
	S.e.	175.65	0.07%	0.01%	0.01%	0.30%	0.03%

Table 3
Performance persistence and fund visibility.
The table reports the estimated coefficients of monthly regressions of fund annual performance on past annual performance and selected fund characteristics in the 1996-2010 period. Risk-adjusted performance is estimated using Carhart's (1997) four-factor model. α denotes performance over the prior 12 months. Size denotes the natural logarithm of the fund's assets under management, lagged one year. flow is the net growth in fund's assets during the last 12 months. age is the natural logarithm of the number of months since the inception date of the fund's oldest class, fam_size and fam_age, denote the size the fund's family and the age of the oldest class in the fund's family. F-load and B-load denote the fund's asset-weighted front-end load and back-end load, lagged one year, respectively. turnover denotes the fund's asset-weighted turnover. Regressors include month dummies. HI is a dummy variable that equals one if the fund belongs to the top quartile of the monthly distribution of: the number of investment categories in the family (column 2); family size (column 3); family age (column 4); or family advertising (column 5). LO is defined analogously for the bottom quartile, except in column 4 where it equals one if the fund's family has no reported advertising expenditures. Standard errors are clustered by both fund and month. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

	(1)	(2) #Inv Cat	(3) Family Size	(4) Family Age	(5) Family Adv.
α	0.071***	0.085***	0.088***	0.090***	0.113***
	(0.019)	(0.022)	(0.023)	(0.022)	(0.029)
size	-0.003***	-0.003***	-0.003***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
flow	-0.005**	-0.005**	-0.005**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
age	0.000	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
fam_size	0.001**	0.001**	0.003***	0.001**	0.001
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
fam_age	-0.000	-0.000	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
F-load	0.021	0.026	0.021	0.024	0.032
	(0.034)	(0.034)	(0.034)	(0.034)	(0.038)
B-load	-0.329***	-0.317***	-0.335***	-0.328***	-0.315***
	(0.106)	(0.105)	(0.106)	(0.105)	(0.122)
exp	-0.619**	-0.615**	-0.554**	-0.637**	-0.551*
	(0.275)	(0.275)	(0.277)	(0.275)	(0.295)
turnover	-0.003*	-0.003*	-0.003*	-0.003*	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
α x LO		-0.076**	-0.059*	-0.078***	-0.052**
		(0.031)	(0.031)	(0.030)	(0.026)
α x HI		-0.015	-0.018	-0.021	-0.048
		(0.025)	(0.025)	(0.022)	(0.049)
LO		0.003	0.006**	-0.003	-0.005***
		(0.002)	(0.003)	(0.003)	(0.002)
HI		0.001	-0.004*	-0.001	-0.001
		(0.002)	(0.002)	(0.002)	(0.003)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	108,524	108,524	108,524	108,524	101,098
Adjusted R-squared	0.074	0.075	0.075	0.074	0.076

Table 4
Performance persistence: the role of fund size and investment categories.
The table reports the estimated coefficients of monthly regressions of fund annual performance on past annual performance and selected fund characteristics in the 1996-2010 period. Risk-adjusted performance is estimated using Carhart's (1997) four-factor model. α denotes performance over the prior 12 months. Size denotes the natural logarithm of the fund's assets under management, lagged one year. flow is the net growth in fund's assets during the last 12 months. age is the natural logarithm of the number of months since the inception date of the fund's oldest class, fam_size and fam_age, denote the size the fund's family and the age of the oldest class in the fund's family. F-load and B-load denote the fund's asset-weighted front-end load and back-end load, lagged one year, respectively. turnover denotes the fund's asset-weighted turnover. Regressors include dummy variables for months, investment categories, and interactions of investment categories with performance. HI is a dummy variable that equals one if the fund belongs to the top quartile of the monthly distribution of: the number of investment categories in the family (column 2); family size (column 3); family age (column 4); or family advertising (column 5). LO is defined analogously for the bottom quartile, except in column 4 where it equals one if the fund's family has no reported advertising expenditures. Standard errors are clustered by both fund and month. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

	(1)	(2) #Inv Cat	(3) Family Size	(4) Family Age	(5) Family Adv.
α	0.171***	0.186***	0.181***	0.185***	0.221***
	(0.043)	(0.044)	(0.044)	(0.045)	(0.058)
size	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
flow	-0.005**	-0.005**	-0.005**	-0.005**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
age	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
fam_size	0.001***	0.002***	0.003***	0.001***	0.001*
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
fam_age	-0.000	-0.000	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
F-load	0.025	0.029	0.026	0.027	0.036
	(0.034)	(0.034)	(0.034)	(0.034)	(0.038)
B-load	-0.339***	-0.328***	-0.349***	-0.340***	-0.324***
	(0.103)	(0.103)	(0.104)	(0.102)	(0.117)
exp	-0.622**	-0.618**	-0.552**	-0.626**	-0.567**
	(0.260)	(0.260)	(0.263)	(0.259)	(0.277)
turnover	-0.002	-0.002	-0.002	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
α x LO		-0.096***	-0.089***	-0.088***	-0.058**
		(0.028)	(0.031)	(0.030)	(0.025)
α x HI		0.005	0.019	-0.004	-0.028
		(0.025)	(0.027)	(0.022)	(0.047)
LO		0.002	0.005*	-0.003	-0.006***
		(0.002)	(0.003)	(0.003)	(0.002)
HI		0.000	-0.003	-0.001	-0.001
		(0.002)	(0.002)	(0.002)	(0.003)
α x size	-0.003	-0.008	-0.016*	-0.007	-0.005
	(0.007)	(0.007)	(0.009)	(0.007)	(0.007)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Inv. Cat. Fixed Effects	Yes	Yes	Yes	Yes	Yes
Inv. Cat. Interactions	Yes	Yes	Yes	Yes	Yes
Observations	108,524	108,524	108,524	108,524	101,098
Adjusted R-squared	0.090	0.091	0.091	0.091	0.094

Table 5

Performance persistence among winners and losers.

The table reports the estimated coefficients of monthly regressions of fund annual performance on past annual performance and selected fund characteristics in the 1996-2010 period. Risk-adjusted performance is estimated using Carhart's (1997) four-factor model. α denotes performance over the prior 12 months. dec_n is a dummy variable that equals one if the fund belongs to the n-th decile of the monthly distribution of past performance. Coefficients for control variables are not reported. Controls include: size, flow, age, family size, family age, front-end and back-end loads, and portfolio turnover, as defined in Table 3. Regressors include month dummies. HI is a dummy variable that equals one if the fund belongs to the top quartile of the monthly distribution of: the number of investment categories in the family (column 2); family size (column 3); family age (column 4); or family advertising (column 5). LO is defined analogously for the bottom quartile, except in column 4 where it equals one if the fund's family has no reported advertising expenditures. Standard errors are clustered by both fund and month. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

	(1)	(2) #Inv Cat	(3) Family Size	(4) Family Age	(5) Family Adv.
dec_1(α)(bottom)	-0.008***	-0.012***	-0.010***	-0.009***	-0.009*
	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
dec_2(α)	-0.004***	-0.005***	-0.003*	-0.005**	-0.006*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
dec_3(α)	-0.003***	-0.003***	-0.003**	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
dec_8(α)	0.003***	0.003**	0.003**	0.003**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
dec_9(α)	0.006***	0.006***	0.008***	0.007***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
dec_10(α)(top)	0.010***	0.014***	0.015***	0.014***	0.020***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.006)
dec_1(α) x LO		0.012**	0.010**	0.009*	0.000
		(0.005)	(0.005)	(0.005)	(0.005)
dec_2(α) x LO		0.003	-0.000	0.002	0.003
		(0.003)	(0.003)	(0.003)	(0.003)
dec_3(α) x LO		0.006***	0.003	0.007**	-0.001
		(0.002)	(0.002)	(0.003)	(0.002)
dec_1(α) x HI		0.006	-0.003	-0.001	0.017**
		(0.004)	(0.004)	(0.004)	(0.008)
dec_2(α) x HI		0.002	-0.003	0.001	-0.002
		(0.003)	(0.003)	(0.003)	(0.007)
dec_3(α) x HI		-0.001	-0.001	-0.001	-0.003
		(0.002)	(0.002)	(0.002)	(0.005)
dec_8(α) x LO		-0.004*	-0.004*	-0.004	0.001
		(0.002)	(0.002)	(0.002)	(0.002)
dec_9(α) x LO		-0.001	-0.004	-0.004	-0.003
		(0.003)	(0.003)	(0.003)	(0.003)
dec_10(α) x LO		-0.016***	-0.014***	-0.011**	-0.013**
		(0.005)	(0.005)	(0.005)	(0.005)
dec_8(α) x HI		0.003	0.001	0.002	0.011**
		(0.002)	(0.002)	(0.002)	(0.004)
dec_9(α) x HI		0.003	-0.004	-0.000	0.004
		(0.003)	(0.003)	(0.003)	(0.005)
dec_10(α) x HI		-0.005	-0.008	-0.007	-0.001
		(0.005)	(0.006)	(0.005)	(0.010)
LO		0.004*	0.008***	-0.002	-0.003*
		(0.002)	(0.003)	(0.002)	(0.002)
HI		-0.000	-0.002	-0.001	-0.002
		(0.002)	(0.002)	(0.002)	(0.003)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	108,524	108,524	108,524	108,524	101,098
R-squared	0.076	0.077	0.078	0.077	0.079

Table 6

Performance persistence for recent winners and losers. Fund returns.

The table reports the estimated coefficients of monthly regressions of fund annual performance on past annual performance and selected fund characteristics in the 1996-2010 period. Risk-adjusted performance is estimated using Carhart's (1997) four-factor model. *ret* denotes fund returns in the last 12 months. dec_n is a dummy variable that equals one if the fund belongs to the n-th decile of the monthly distribution of past performance. Coefficients for control variables are not reported. Controls include: size, flow, age, family size, family age, front-end and back-end loads, and portfolio turnover, as defined in Table 3. Regressors include month dummies. HI is a dummy variable that equals one if the fund belongs to the top quartile of the monthly distribution of: the number of investment categories in the family (column 2); family size (column 3); family age (column 4); or family advertising (column 5). LO is defined analogously for the bottom quartile, except in column 4 where it equals one if the fund's family has no reported advertising expenditures. Standard errors are clustered by both fund and month. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

	(1)	(2) #Inv Cat	(3) Family Size	(4) Family Age	(5) Family Adv.
dec_1(ret)	-0.009***	-0.013***	-0.012***	-0.012***	-0.009
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
dec_2(ret)	-0.004***	-0.006***	-0.007***	-0.004**	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
dec_3(ret)	-0.003**	-0.004**	-0.003**	-0.003*	0.000
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
dec_8(ret)	0.000	-0.000	-0.001	0.001	0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
dec_9(ret)	0.002	0.001	0.002	0.003	0.007*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
dec_10(ret)	0.003	0.003	0.003	0.005	0.006
	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)
dec_1(ret) x LO		0.012***	0.010**	0.012***	-0.001
		(0.004)	(0.004)	(0.005)	(0.005)
dec_2(ret) x LO		0.009***	0.008**	0.005*	-0.000
		(0.003)	(0.003)	(0.003)	(0.004)
dec_3(ret) x LO		0.005	0.003	0.005*	-0.003
		(0.003)	(0.003)	(0.003)	(0.003)
dec_1(ret) x HI		0.011**	0.001	0.003	-0.002
		(0.004)	(0.005)	(0.005)	(0.010)
dec_2(ret) x HI		0.003	0.003	-0.004	-0.001
		(0.003)	(0.003)	(0.003)	(0.006)
dec_3(ret) x HI		0.002	0.001	-0.003	-0.001
		(0.002)	(0.002)	(0.002)	(0.005)
dec_8(ret) x LO		0.000	0.002	-0.001	-0.002
		(0.003)	(0.002)	(0.003)	(0.003)
dec_9(ret) x LO		0.000	0.002	-0.003	-0.006
		(0.003)	(0.004)	(0.003)	(0.004)
dec_10(ret) x LO		-0.002	0.001	-0.002	-0.004
		(0.005)	(0.005)	(0.005)	(0.005)
dec_8(ret) x HI		0.002	0.002	-0.003	-0.003
		(0.002)	(0.002)	(0.002)	(0.005)
dec_9(ret) x HI		0.002	-0.004	-0.003	-0.004
		(0.003)	(0.003)	(0.003)	(0.005)
dec_10(ret) x HI		0.002	-0.003	-0.004	-0.000
		(0.006)	(0.005)	(0.004)	(0.010)
LO		0.001	0.004	-0.003	-0.003
		(0.002)	(0.003)	(0.003)	(0.002)
HI		-0.001	-0.004*	0.000	0.001
		(0.002)	(0.002)	(0.002)	(0.003)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	108,524	108,524	108,524	108,524	101,098
Adjusted R-squared	0.073	0.074	0.074	0.074	0.075

Table 7

Performance persistence for recent winners and losers. Retail versus institutional funds.

The table reports the estimated coefficients of monthly regressions of fund annual performance on past annual performance and selected fund characteristics in the 1996-2010 period. Risk-adjusted performance is estimated using Carhart's (1997) four-factor model. *ret* denotes fund returns in the last 12 months. dec_*n* is a dummy variable that equals one if the fund belongs to the *n*-th decile of the monthly distribution of past performance. Coefficients for control variables are not reported. Controls include: size, flow, age, family size, family age, front-end and back-end loads, and portfolio turnover, as defined in Table 3. Regressors include month dummies. HI is a dummy variable that equals one if the fund belongs to the top quartile of the monthly distribution of: the number of investment categories in the family (columns 1 & 5); family size (column 2 & 6); family age (column 3 & 7); or family advertising (columns 4 & 8). LO is defined analogously for the bottom quartile, except in columns 4 and 8 where it equals one if the fund's family has no reported advertising expenditures. Standard errors are clustered by both fund and month. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

	Retail Funds				Institutional Funds			
	(1) #Inv. Cat.	(2) Fam. Size	(3) Fam. Age	(4) Fam. Adv.	(5) #Inv. Cat.	(6) Fam. Size	(7) Fam. Age	(8) Fam. Adv.
dec_1(α)(bot.)	-0.012***	-0.017***	-0.012**	-0.009	-0.011***	-0.004	-0.007*	-0.010*
	(0.004)	(0.004)	(0.005)	(0.007)	(0.003)	(0.004)	(0.004)	(0.006)
dec_2(α)	-0.007***	-0.006**	-0.008***	-0.008	-0.003*	-0.001	-0.000	-0.004
	(0.002)	(0.003)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)	(0.004)
dec_3(α)	-0.004**	-0.003*	-0.005**	-0.000	-0.003**	-0.003*	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)
dec_8(α)	0.005**	0.004	0.004**	-0.002	0.002	0.003	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
dec_9(α)	0.005*	0.007**	0.007***	0.004	0.006***	0.009***	0.007***	0.011***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)
dec_10(α)(top)	0.012**	0.015***	0.012***	0.018**	0.015***	0.014***	0.015***	0.020***
	(0.005)	(0.005)	(0.004)	(0.008)	(0.005)	(0.004)	(0.005)	(0.008)
dec_1(α) x LO	0.013**	0.017***	0.015*	-0.001	0.011	-0.001	0.001	0.002
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.006)
dec_2(α) x LO	0.004	0.001	0.008*	0.004	0.003	0.003	-0.005	0.003
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
dec_3(α) x LO	0.006**	0.002	0.008*	-0.002	0.008*	0.008*	0.006	-0.001
	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)
dec_1(α) x HI	-0.015*	0.002	-0.007	-0.003	0.018***	-0.007	0.002	0.032***
	(0.008)	(0.007)	(0.007)	(0.010)	(0.005)	(0.006)	(0.005)	(0.008)
dec_2(α) x HI	-0.004	-0.004	0.002	-0.014	0.005*	-0.002	-0.001	0.006
	(0.005)	(0.005)	(0.004)	(0.011)	(0.003)	(0.004)	(0.003)	(0.009)
dec_3(α) x HI	-0.002	-0.001	0.001	-0.005	0.001	-0.000	-0.001	0.000
	(0.004)	(0.003)	(0.003)	(0.007)	(0.002)	(0.002)	(0.003)	(0.006)
dec_8(α) x LO	-0.005*	-0.005	-0.003	0.005	-0.003	-0.002	-0.004	-0.001
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
dec_9(α) x LO	0.001	-0.002	-0.003	0.001	-0.007	-0.008*	-0.005	-0.006*
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)
dec_10(α) x LO	-0.013**	-0.014**	-0.008	-0.010	-0.025***	-0.010	-0.015**	-0.016**
	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)	(0.009)	(0.007)	(0.008)
dec_8(α) x HI	-0.000	0.002	-0.001	0.018***	0.005*	0.000	0.005**	0.003
	(0.003)	(0.004)	(0.003)	(0.007)	(0.003)	(0.003)	(0.003)	(0.005)
dec_9(α) x HI	0.002	-0.003	-0.001	0.008	0.003	-0.005	-0.000	0.002
	(0.005)	(0.004)	(0.004)	(0.008)	(0.004)	(0.003)	(0.004)	(0.006)
dec_10(α) x HI	0.007	-0.003	-0.004	0.014	-0.015**	-0.011	-0.013*	-0.009
	(0.008)	(0.008)	(0.006)	(0.014)	(0.006)	(0.007)	(0.007)	(0.009)
LO	0.006**	0.005	-0.001	-0.000	-0.002	0.008*	-0.003	-0.005**
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)
HI	0.001	-0.001	0.006**	-0.002	-0.001	-0.004	-0.007***	-0.002
	(0.003)	(0.004)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)
Obs.	55,214	55,214	55,214	48,643	53,310	53,310	53,310	52,455
Adj. R-sq	0.071	0.070	0.070	0.069	0.104	0.103	0.105	0.105

Table 8

Performance persistence for recent winners and losers. High-excess-fee versus low-excess-fee funds.

The table reports the estimated coefficients of monthly regressions of fund annual performance on past annual performance and selected fund characteristics in the 1996-2010 period. Risk-adjusted performance is estimated using Carhart's (1997) four-factor model. *ret* denotes fund returns in the last 12 months. dec_n is a dummy variable that equals one if the fund belongs to the n-th decile of the monthly distribution of past performance. Coefficients for control variables are not reported. Controls include: size, flow, age, family size, family age, front-end and back-end loads, and portfolio turnover, as defined in Table 3. Regressors include month dummies. HI is a dummy variable that equals one if the fund belongs to the top quartile of the monthly distribution of: the number of investment categories in the family (columns 1 & 5); family size (column 2 & 6); family age (column 3 & 7); or family advertising (columns 4 & 8). LO is defined analogously for the bottom quartile, except in columns 4 and 8 where it equals one if the fund's family has no reported advertising expenditures. Standard errors are clustered by both fund and month. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

	High Excees Fee				Low Excees Fee			
	(1) #Inv. Cat.	(2) Fam. Size	(3) Fam. Age	(4) Fam. Adv.	(5) #Inv. Cat.	(6) Fam. Size	(7) Fam. Age	(8) Fam. Adv.
dec_1(α)(bot.)	-0.011**	-0.007	-0.008*	-0.015*	-0.016**	-0.013**	-0.016**	-0.011
	(0.005)	(0.005)	(0.005)	(0.008)	(0.006)	(0.006)	(0.008)	(0.010)
dec_2(α)	-0.005	-0.001	-0.004	-0.001	-0.001	0.000	-0.002	-0.008
	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.003)	(0.007)
dec_3(α)	-0.005**	-0.002	-0.004	-0.002	-0.001	-0.000	-0.003	0.001
	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)
dec_8(α)	0.003	0.004	0.002	-0.004	0.002	0.003	0.005**	0.003
	(0.003)	(0.003)	(0.003)	(0.005)	(0.002)	(0.002)	(0.002)	(0.005)
dec_9(α)	0.005	0.010**	0.002	0.006	0.007**	0.008**	0.011***	0.013**
	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)
dec_10(α)(top)	0.012**	0.019***	0.013**	0.022***	0.015***	0.017***	0.015**	0.023***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.005)	(0.006)	(0.006)	(0.007)
dec_1(α) x LO	0.028***	0.022***	0.023***	0.007	0.005	-0.007	0.003	-0.005
	(0.009)	(0.008)	(0.008)	(0.009)	(0.010)	(0.009)	(0.012)	(0.010)
dec_2(α) x LO	0.007	0.000	0.009	-0.004	0.001	-0.002	0.007	0.011
	(0.007)	(0.007)	(0.008)	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)
dec_3(α) x LO	0.019***	0.010	0.015*	0.000	0.005	0.000	0.009**	0.000
	(0.007)	(0.007)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
dec_1(α) x HI	0.002	-0.012	-0.003	0.045***	0.015	0.016*	0.010	0.049***
	(0.007)	(0.008)	(0.007)	(0.013)	(0.012)	(0.008)	(0.010)	(0.014)
dec_2(α) x HI	-0.001	-0.010**	-0.004	0.005	0.005	0.002	0.005	0.012
	(0.005)	(0.005)	(0.005)	(0.011)	(0.005)	(0.005)	(0.005)	(0.011)
dec_3(α) x HI	0.001	-0.006*	-0.001	-0.002	0.004	0.002	0.006	-0.003
	(0.004)	(0.003)	(0.004)	(0.010)	(0.004)	(0.004)	(0.004)	(0.006)
dec_8(α) x LO	0.001	0.004	0.000	0.009**	0.003	-0.000	-0.004	-0.000
	(0.005)	(0.006)	(0.007)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)
dec_9(α) x LO	-0.005	-0.012	0.002	0.000	0.006	0.003	-0.005	-0.006
	(0.007)	(0.007)	(0.009)	(0.006)	(0.005)	(0.006)	(0.004)	(0.005)
dec_10(α) x LO	-0.021**	-0.026***	-0.013	-0.016*	-0.009	-0.011	-0.007	-0.015**
	(0.009)	(0.009)	(0.010)	(0.008)	(0.008)	(0.009)	(0.007)	(0.006)
dec_8(α) x HI	0.006	0.001	0.007	0.015**	0.000	0.001	-0.005	0.006
	(0.004)	(0.005)	(0.004)	(0.007)	(0.004)	(0.004)	(0.004)	(0.006)
dec_9(α) x HI	0.007	-0.008	0.012**	0.004	-0.001	-0.004	-0.006	-0.004
	(0.006)	(0.006)	(0.005)	(0.010)	(0.004)	(0.005)	(0.005)	(0.006)
dec_10(α) x HI	0.005	-0.020**	-0.006	-0.010	-0.011	-0.013*	-0.007	-0.012
	(0.010)	(0.009)	(0.009)	(0.013)	(0.008)	(0.008)	(0.008)	(0.009)
LO	-0.000	0.004	-0.005	-0.010**	0.006	0.007*	-0.001	0.001
	(0.005)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
HI	-0.008**	-0.003	-0.010**	-0.012	0.002	0.003	0.005	0.003
	(0.004)	(0.005)	(0.005)	(0.008)	(0.003)	(0.004)	(0.004)	(0.004)
Obs.	26,970	26,970	26,970	25,185	27,207	27,207	27,207	25,284
Adj. R-sq	0.096	0.098	0.096	0.099	0.066	0.067	0.065	0.064