Capital Commitment and Investment Decisions: The Role of Mutual Fund Charges *

Juan-Pedro Gómez[†] Melissa Porras Prado[‡]

Rafael Zambrana[§]

September 8, 2020

Abstract

Many investors purchase open-end mutual funds through intermediaries, paying brokers and financial advisors for fund distribution and advice via alternative sale charge fee structures. We argue that the fee structure choice reveals valuable information about investors horizon. That allows portfolio managers to manage liquidity more efficiently, and to improve performance by timely matching their investment choices to the underlying investment horizon of their investors. Mutual funds with more committed capital hold shares longer, invest in more illiquid stocks, and take advantage of securities with slow-moving arbitrage opportunities, i.e., fire-sale stocks, innovative stocks. This evidence reveals an overlooked shadow cost of disintermediation in the mutual fund industry.

JEL Classification Codes: G11, G23, J33, J44, L22, L25, L84, M12, M52
Keywords: Mutual fund, intermediaries, investment horizon, liquidity management, fee structure

*This work was funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209), POR Norte (Social Sciences DataLab, Project 22209), and the Spanish Ministry of Economy and Competitiveness (MCIU), State Research Agency (AEI), and European Regional Development Fund (ERDF) Grant No. PGC2018-101745-A-I00. Juan-Pedro thanks the Bank of Spain for its generous support. We thank Tim Adam, Guillermo Baquero, Gjergji Cici, Richard Evans, Miguel Ferreira, Alexander Kempf, Vikram Nanda, Arthur Petit-Romec, Clemens Sialm, David Stolin, and Neal Stoughton for their helpful comments. We thank Giorgio Ottonello for his help in gathering mutual fund prospectus information. We thank Ron Kaniel and Robert Parham, and Brad Barber and Terrance Odean for sharing their data with us. We thank seminar participants at the 2019 Finance Forum at Carlos III University, Bauer/Houston University, CFR Cologne University, Eller/University of Arizona, Jindal/UT at Dallas, Darden/University of Virginia, ESMT/Humboldt University, the 2019 Lubrafin Conference, McCombs/UT at Austin, Nova SBE, Skema Business School, Universitat Illes Balears, Hebrew University of Jerusalem, and Universidad Autónoma de Madrid.

[†]IE Business School at IE University in Madrid, Spain. Email: juanp.gomez@ie.edu
[‡]Nova School of Business and Economics. Email: melissa.prado@novasbe.pt
[§]University of Notre Dame. Email: rzambra2@nd.edu

I Introduction

Investors can purchase mutual fund shares through different channels. If the investment takes place through a financial advisor or the fund is distributed by a broker or dealer (who may be the same as the advisor), share classes usually include a load fee.[1] Investors can also buy no-load shares, which have no sales charges. No-load shares are traditionally associated with funds sold directly to the investor. More recently, though, broker-sold funds may also offer no-load shares to investors.

There is ample evidence that broker-sold funds underperform the average actively managed fund (Bergstresser, Chalmers, and Tufano (2009)) as their managers either have weaker incentives to generate alpha (Del Guercio and Reuter (2014)); prioritize their compensation incentives over those of their clients (Christoffersen, Evans, and Musto (2013) and Chalmers and Reuter (2020))); or cater to a clientele that values nonperformance characteristics (Del Guercio and Tkac (2010)). These articles, however, are silent about the information conveyed to managers by investors' choice among different share classes.

We document that mutual fund intermediaries can add value by operating on information that clients convey about ex-ante commitment to hold investments longer, through their choice among sale charge fees. This information allows mutual fund managers to better anticipate flows and to capitalize on slow-moving arbitrage opportunities and the return premium on illiquid assets. Our findings reveal a long-term "shadow cost" of disintermediation in the mutual fund industry, a phenomenon that may shape the investment decisions of portfolio managers.

The decoupling of financial advice and investment together with recent demand for passive (and cheaper) financial assets like exchange-traded funds has put strong pressure on mutual fund fees and in particular on front- and back-end load fees.[2] Given the

[1]There are broadly three load fee structures. Class A shares charge a relatively high front-end sales fee when the shares are purchased and a relatively low annual level fee (also known as 12b-1 fee). Class B shares have a lower or no front-end fee but include a contingent deferred sales charge (CDSC) to be paid when shares are redeemed. This charge can be waived if the investment is held for a long predetermined period. The annual level fee, in this case, is usually higher than that of the first structure. Finally, investors may pay a relatively higher annual level fee for Class C shares, but they are exempt from paying a front-end load fee. This structure may include a relatively low CDSC if the shares are liquidated during the first year.

[2]Barber, Odean, and Zheng (2005) suggest that management companies are replacing one-off explicit load fees with higher periodic operating costs, which investors find more difficult to isolate and identify.

evidence on the underperformance of broker-sold funds, mutual fund investors should find it advantageous to invest in mutual funds without paying explicit load fees for financial advice. Our research challenges this view.

We conjecture that investors who select share classes with sizeable front- or back-end load fees reveal a rational ex-ante capital commitment to hold such an investment longer than investors who select share classes with no front- or back-end loads but higher annual fees (henceforth level-load shares) or investors in no-load shares. Thus a fund manager can infer a capital commitment from these investors. If our conjecture is right, we expect manager behavior, investment strategies, and ultimately fund performance, to be affected by fund investors' choices among investment fee structures.

We examine actively managed US domestic equity mutual funds over the 1992-2016 period. For each fund and each month in our sample, we define *Capital Commitment* as the proportion of a fund's total net assets (TNA) that comes from share classes with sizeable front- or back-end loads. Analogously, we define no-load and level-load investors to constitute the proportion of a fund's TNA that comes from no-load and level-load shares, respectively.

Whether investor choice among fee structures reveals capital commitment is ultimately an empirical question. In principle, when financial advisors guide investors in their share class choice, a key element should be how long the investor *expects* to hold the shares. Yet, the literature has shown that financial advisors may have incentives to guide investors into share classes that maximize advisor long-term fees rather than those that better suit the investment horizon of their clients. Sophisticated investors may also avoid load fees altogether, whatever their investment horizon (Del Guercio and Reuter (2014)), while the choice of front-load fee shares may be driven by discounts in the sales fee if the initial or future invested amount surpasses certain breakpoints, regardless of the investor's horizon.

First, we find that higher capital commitment is associated with lower fund flow volatility. Additionally, managers in funds with a higher proportion of capital commitment can predict more accurately future flows by adjusting their current cash holdings to time them. Altogether, we interpret this as evidence that, inspite of the underlying conflicts of interests between brokers and investors, fund flows are more stable and predictable when the percentage of TNA that comes from front- and back-end load shares increases, consistent with higher capital commitment.[3]

Second, using the portfolio duration measure of Cremers and Pareek (2016), we show that managers increase their duration when the fund's capital commitment is higher.[4] This suggests that managers exploit their investors's commitment to hold their investment for a longer period. We then investigate the performance implication of this commitment. Funds with higher capital commitment exhibit higher alpha. This result is robust when we control for institutional investors and, importantly, for no-load funds, arguably more likely to be sold directly. In other words, among load-share funds (more likely to be distributed through brokers or dealers), those with higher capital commitment perform better. This finding is robust when we control for the evaluation period of portfolio managers who receive performance-based compensation (as a proxy for managerial explicit incentives), funds with redemption fees (as a substitute for capital commitment), and managers' evaluation period (to capture career incentives). Then, we decompose fund holding duration into the part projected by the fund's committed capital and the part orthogonal to committed capital. Our tests confirm that only the projected part predicts fund outperformance over long-term investment horizons. This is consistent with the idea that patient investment strategies is indeed related to superior performance, but only when managers match their portfolio horizon to the investment horizon of the underlying investors.[5]

Thrid, we explore the potential channels through which more stable capital affects both the investment choices of portfolio managers and fund performance. We find that managers of funds with more committed capital benefit from an illiquidity return premium (Amihud (2002)) because they can hold more illiquid stocks and reduce portfolio turnover. They also capitalize on the return predictability associated with stocks in which research and development (R&D) investment is more intense.[6] Finally, following Ed-

[3]These results hold when we consider front- and back-end load fees separately, suggesting that managers interpret both load shares as *ex-ante* capital commitment. They are similar after we exclude no-load share classes from the control group, hence compare only load funds. This alleviates concerns that we are capturing unobservable differences across load versus no-load share classes. Results remain robust after we control for the holdings of institutional investors (as a proxy for sophisticated investors).

[4]Results are similar when we use the horizon measures of Lan, Moneta, and Wermers (2015).

[5]We also examine fund risk exposure to capital commitment. We find that funds with more committed capital are more sensitive to aggregate market liquidity as captured by the factor of Pastor and Stambaugh (2003), and to the long-horizon mispricing factors of Daniel, Hirshleifer, and Sun (2019). These results are consistent with the idea that capital commitment allows mutual funds to exploit slow-moving arbitrage opportunities.

[6]Chan, Lakonishok, and Sougiannis (2001) and Lev and Sougiannis (1996) demonstrate that firms with high ratios of R&D relative to market equity earn high subsequent returns; Eberhart, Maxwell,

mans, Goldstein, and Jiang (2012), we construct a flow-induced pressure variable at the stock level, conditional on outflows, and find that funds with more committed capital invest more in fire-sale stocks in the next quarter.[7] Overall, our portfolio holding results show that capital commitment is conducive to long-term risky arbitrage.

We perform a set of robustness tests and discuss alternative explanations of our results. To address potential endogeneity concerns, we use the discontinuity in the supply of capital (mostly level-load shares) from the *Wall Street Journal (WSJ)* "Category Kings" ranking list analyzed in Kaniel and Parham (2017). Our results remain unchanged and confirm that capital commitment influences portfolio managers' investment choices. We then explore if higher capital commitment shows an asymmetric performance-sensitivity with respect to fund over(under) performance, consistently with capital commitment as a proxy for investor sophistication. The results are inconsistent with this alternative explanation. Finally, we analyze a household-level data set from a large US brokerage house collected by Barber and Odean (2001). The choice of load fee structure reveals information about households' capital commitment beyond what the manager can potentially gather from investors' characteristics when they hire the broker (Johnson (2004)). Finally, as further evidence that management companies value the information revealed by the investors share class choice, we show that they are more explicit about the fund's long-term investment behaviour in the prospectus after the fund family starts offering no-load shares.

Our work contributes to several strands of the literature. We add to the literature that stresses the importance of liquidity management for mutual fund managers (Coval and Stafford (2007), Agarwal and Zhao (2020), and Chernenko and Sunderam (2016)). We show that fee structures can help portfolio managers better anticipate and manage flows. The information embedded in investor choice of fee structure helps managers deliver per-

and Siddique (2004) find that large increases in R&D expenditures predict positive future abnormal returns, and Hirshleifer, Hsu, and Li (2013) show that firm-level innovative "efficiency" (measured as patents scaled by R&D investment) forecasts future returns. Cohen, Diether, and Malloy (2013) suggest the mechanism behind the stock return predictability is likely to be the misvaluation of R&D ability. Such misvaluation is more likely to be reaped by long-term investors, as complexity in information processing can lead to a significant delay in impounding of information into asset prices, as argued by Lauren and Dong (2012), and portfolio managers with short-term horizons have fewer incentives to invest in information acquisition about firms' long-term projects (Dow and Gorton (1994) and Goldman and Slezak (2003)).

[7]There is evidence that mispriced stocks are riskier for short-term investors and profitable only in the long run. For instance, Coval and Stafford (2007) show that corrections in stocks sold by outflow-distressed mutual funds can take up to two years, while Giannetti and Kahraman (2018) find that closed-end funds are more likely to purchase fire sale stocks than open-ended funds.

formance by efficiently matching their portfolio strategy to the underlying investment horizon of the investor. This helps explain why asset management companies and investors continue to use these financial intermediaries even in the face of reported conflicts of interest (Christoffersen, Evans, and Musto (2013)) or underperformance (Del Guercio and Reuter (2014)). Financial intermediaries can add value related to share-class decisions, much more than in selection across funds.

Our findings suggest that an optimal matching of investor and fund investment horizon can help to overcome a serious impediment to arbitrage that arises in the open-ended mutual fund structure. Stein (2005) argues that competition for investor funds and information asymmetry about managers' ability may lead to more open-end funds, which are subject to a higher risk of early redemption, at the cost of profitable, unexploited long-term arbitrage opportunities. Giannetti and Kahraman (2018) present empirical evidence consistent with this hypothesis by comparing portfolio choices of open-end versus closed-end funds. Closed-end funds are found to purchase more underpriced stocks with high arbitrage risk than open-end funds. Open-ended funds are nonetheless the dominant organizational structure in the asset management industry both in size and number.[8] Thus it is important to understand information embedded in load fees and how this pricing mechanism can give mutual fund managers more freedom to pursue different investment strategies. We claim that funds with more committed capital are better equipped to engage in long-term risky arbitrage.

Our results are distinct from hedge fund research on the risk of early liquidation and its impact on portfolio choices and performance. Aragon (2007) and Agarwal, Daniel, and Naik (2009), for instance, show that managers in funds with lock-up provisions outperform those without them by exploiting a liquidity premium. We add to this literature by discussing the importance of the fee structure for mutual fund managers; that is, mutual funds with more committed capital outperform. An important difference is that, unlike in mutual funds, hedge funds impose explicit restrictions on investors. Our results suggest that efficiently matching mutual fund investor horizons, and not necessarily locking investors in, is what drives outperformance.

Finally, we also contribute to the literature on managerial myopia or short-termism by demonstrating the important role for the horizon of the underlying capital. Agarwal,

[8]According to the 2018 ICI Factbook, the total volume of assets in open-end mutual funds was $18.3 trillion, while the volume of closed-end mutual funds was $275 billion.

Vashishtha, and Venkatachalam (2018) for instance, show that managers may overlook profitable long-term investments for career concern reasons. They show that recent regulation forcing higher disclosure of managers' portfolio holdings exacerbates this concern and causes less investment in R&D in firms where institutional investors have a significant stake. We also investigate the interaction between institutional investors and R&D capital, where we show that underlying mutual fund investor short-termism may induce portfolio managers to reduce their exposure to firms with longer-term prospects for success.

The paper is organized as follows. Section II describes the data used. We then present the impact of capital commitments on investor behavior in Section III. Section IV analyzes the portfolio manager's investment strategy and performance. Finally, in Section V we check the robustness of our results and discuss alternative interpretations. Section VI concludes.

II Data

We examine actively managed US domestic equity mutual funds over the 1992-2016 period. Our sample comprises 3,955 funds across 899 asset management companies. We use the CRSP Survivorship-Bias Free Mutual Funds Database to obtain fund and management company information, including fund load structure information and general fund characteristics. We collect fund level inflows (sales) and outflows (redemption) data from N-SAR question 28a-f. Redemption fees data come from Morningstar. We measure fund holding durations as in Cremers and Pareek (2016). We also use portfolio holdings from Thomson Reuters Mutual Fund Holdings database (S12) to construct holdings-based trading horizon measures as in Lan, Moneta, and Wermers (2015). All stock-level price information is from CRSP, and the accounting variables come from Compustat. We use the *Wall Street Journal* "Category Kings" ranking list from Kaniel and Parham (2017).

We create our primary independent variable using the share classification system of the Investment Company Institute (ICI). For every fund, we define *Capital Commitment* as the fraction of the fund's total TNA that comes from front- and back-end load shares in a given period. All variables are defined in Table A1 of the Appendix.

[Insert Figure 1 about here]

Panel A of Table 1 reports the sample mean, standard deviation, and distribution of TNA by share class. On average, 31.70% of fund TNA qualify as capital commitment, of which 26.24% have front-end loads and 5.46% back-end loads. Level share classes represent on average about 20% of fund TNA, and 38% of TNA is in no-load shares. Figure 1 illustrates the divergent trends of front-end and no-load share classes in the sample. Back-end load shares have become negligible while the proportion of level-load shares, although still sizeable, has been declining since 2005.

Panel B reports fund and family characteristics. The average fund has USD 1,948 million total net assets (TNA), in a family with an average of 161 funds. The average fund is 13 years old and has an annual turnover of 89%. On average, funds have an annual expense ratio of 1.28% and turnover of 89% per year. They hold about 5% of their assets under management in cash and their average gross return is about 0.9% per month. In terms of fees, the average front (back) load is 4% (2%). On average, 22% of the fund's assets belong to institutional investors and about 17% of funds have a redemption fee.

[Insert Table 1 about here]

It is worth noting that our share-class classification is different from the *direct-sold* versus *broker-sold* classification in the Finance Research Corporation (FRC) data that are used in Bergstresser, Chalmers, and Tufano (2009), Del Guercio and Tkac (2010), and Del Guercio and Reuter (2014). Most notably, our key variable, *Capital Commitment*, varies within direct- and broker-sold funds depending on the proportion of share classes with sizeable front- and back-end loads relative to level-load and no-load shares. Higher capital commitment is certainly associated with a higher likelihood of a broker distribution channel. Yet, two funds identified as broker-sold may have different degrees of capital commitment and thus, we argue, convey different information about investor horizon to their particular managers. Likewise, two funds, one direct-sold and the other broker-sold, may have the same or very similar capital commitment. In general, the mapping between direct-sold and no-load funds, on the one side, and brokered-sold and load funds on the other, is much more blurred nowadays than in the sample period used in the previously cited articles.

American Funds, for instance, is the largest wholesale broker-sold family according to Del Guercio and Tkac (2010). In the process of choosing the best share class "with your financial professional," American Funds claims it is important to consider the investment horizon, the objective, and the amount to invest.[9] Class A American Funds shares carry a front-load and lower annual expenses than other share classes. In the case of class C shares, there is no front-end load, but the annual fees are higher. In November 2016, American Funds decided to issue no-load shares for the first time in what was considered as "the end of an era" of brokered-only investment. On the other side, Fidelity is the largest direct-sold fund family.[10] Fidelity funds are sold in a variety of share classes including load-fee shares (classes A, B, and C) and no-load shares. These funds will vary on their level of capital commitment, even if they are classified as direct-sold.

A potential concern is that our primary variable of interest, *Capital Commitment*, is concentrated mostly in several funds offering only load shares. This would certainly be a problem, as we would not be able to distinguish between the share classes and the funds themselves. Figure 2 shows this is not the case. We classify a fund as a *Multi Share Class* fund if it offers load and no-load share class options (the blue line in Figure 2). The single-share class funds offer only load shares (classified as *Pure Load* funds) or no-load shares (classified as *Pure No-Load* funds), corresponding to the green and red lines in Figure 2, respectively. The percentage of *Multi Share Class* funds has steadily increased during our sample period, reaching more than 50% of funds at the end of the sample period. This has happened mainly at the expense of *Pure Load* funds, which have declined almost monotonically to currently represent slightly more than 20% of the sample. *Pure No-Load* funds have accounted for a relatively stable 20% share of the sample since 2005.

[Insert Figure 2 about here]

There might still be an endogenous choice of share class structures across funds that possibly caters to different types of investors. To tackle this issue, we follow a multi-pronged strategy. First, we control for fund and family features in our tests. Second, we show that our results are robust after including fund fixed effects to control for unobservable (fixed) fund characteristics. We also test the robustness of our findings when we remove or control for pure no-load funds. Finally, we instrument the funds'

[9] https://www.americanfunds.com/individual/investments/share-class-information/share-class-pricing.html

[10] https://www.fidelity.com/mutual-funds/all-mutual-funds/fees

capital commitment to capture exogenous variation and identify the effect on portfolio investment strategies.

III Flow Stability and Capital Commitment

We begin by analyzing whether investors' share class choice reflects their investment horizon. Early research on mutual fund share classes points in this direction. Chordia (1996) argues that load fees can be structured to dissuade redemptions, while Nanda, Wang, and Zheng (2009) postulate that the launch of level- and no-load shares may increase the level and volatility of fund inflows and attract investors with short and uncertain investment horizons.

On the other side, more recent research suggest that brokers may prioritize their compensation incentives over the interest of their clients (Christoffersen, Evans, and Musto (2013) and Chalmers and Reuter (2020)). If this conflict is strong enough, ill-advised investors may end up choosing the wrong share class. Additionally, the choice of front-load fee shares may be driven by discounts in the sales fee if the initial or future invested amount surpasses certain breakpoints, independent of the investor's horizon. In all these cases, we expect that share classes reveal no differential information about the underlying investors' horizon. This will be our null hypothesis.

We use two proxies for investors' horizon at the fund level: flow volatility and flow predictability. The underlying assumption is that higher stability in fund flows reflects longer investors' horizon. To test the relation between flow volatility and capital commitment, we run a pooled regression for every fund i and every quarter t:

$$Flow\,Volatility_{\,i,t+24} = \beta_0 + \beta_1 Capital\,Commitment_{\,i,t} + \beta_2 Controls_{\,i,t} + \mu_{i,t} + \epsilon_{i,t}, \quad (1)$$

where *Flow Volatility* is the standard deviation of monthly inflows and outflows obtained from the NSAR filings in the following 24 months. Since our analysis is on a quarterly frequency, for the monthly variables we take the end-of-the-quarter monthly value. *Capital Commitment* is the proportion of total assets under management coming from the addition of front- and back-end load share classes. We also replace *Capital Commitment* with, simultaneously, the variables *Back* and *Front Investors*, which represent the percentage of fund TNA in the corresponding share classes. We standardize all the continuous share class variables to have zero mean and unit standard deviation. We apply this transformation to make it easier to compare each variable's impact, where estimated coefficients denote the impact of a one-standard-deviation change in the explanatory variable.

Controls include: *Fund Size(log), Family Size(log),* the number of *Family Funds(log), Expense Ratio,* the average *Load Fee* and *Fund Age(log).* We also control for the percentage of fund TNA invested by *No-Load* and *Institutional Investors.* $\mu_{i,t}$ represents time $\times$ fund style fixed effects to control for unobservables related to fund manager trading behavior that vary over time and within investment objective. Standard errors are clustered at the fund level.

The object of interest is the coefficient β_1 in equation (1). Under the null hypothesis, the conflict of interest between brokers and investors is strong enough such that the share classes that we identify with higher capital commitment are unrelated to flow volatility. In that case, β_1 should not be different from zero. Column 1 of Table 2 strongly rejects the null hypothesis. Funds with higher capital commitment exhibit, on average, lower fund flow volatility over the following 24 months. A one-standard-deviation increase in capital commitment is associated with 0.118 standard deviations lower flow volatility, which is equivalent to a 21.2% (= $(0.118 \times 0.063)/0.035$) reduction in mean flow volatility. In column 2, we replace the commitment variable in equation (1) with the standardized percentage of the fund's TNA held, separately, by *Back* and *Front Investors.* Flow volatility is significantly lower for every one standard deviation in the percentage of fund TNA in the hands of, respectively, back and front investors, though the effect of front-end loads seems to have a slightly larger impact.

The results remain robust and strongly significant at the 1% level even after controlling for the percentage of TNA invested in no-load shares (in column 3) or held by institutional investors (in column 4). This suggests that our results are not driven by some (no-load) direct-sold fund families or by sophisticated institutional investors, and that both back- and front-end investors indeed contribute to the near-future stability of the fund flows.[11]

[Insert Table 2 about here]

[11] In an additional robustness test, we separate fund flows into inflows and outflows as obtained from NSAR filings. *Flow Volatility* in equation (1) is replaced with, respectively, the volatility (standard deviation in the next 24 months) of monthly inflows, outflows, and net flows in Table A2 of the Appendix. The negative relation between flow volatility and our measure of capital commitment is robust across all specifications.

As a second proxy for investor horizon, we use flow predictability, defined as the manager's ability to anticipate fund flows and, thereby, better manage the fund's liquidity. We measure this ability through the variable *Net Fund Flows Prediction*, defined as the R-squared from the regression of current net fund flows (inflows - outflows) on the cash holdings of the previous month over a rolling window of 36 months. The R-squared captures how portfolio managers adjust their cash balance to fund flows, given what managers know before time t about the investors' horizon. In other words, we test how good managers are at managing cash based on what they learn from investor's share class choice.[12]

Table 3 presents the results of equation (1) after replacing, for each fund i and every quarter t, *Flow Volatility* with *Fund Flows Prediction*. Under the null hypothesis, share class choice is disconnected from the investors' horizon: higher capital commitment fails to improve upon the predictability of fund liquidity needs. If this is true, β_1 should be no statistically different from zero. We standardize all continuous variables for ease of interpretation and use the same controls. The evidence strongly rejects the null hypothesis. A one-standard-deviation increase in capital commitment is associated with 0.064 standard deviations higher prediction ability, which is equivalent to a 10.05% $(= (0.064 \times 0.11)/0.07)$ increase over mean prediction ability. This prediction ability seems to be coming from both back and front-end investor flows. Portfolio managers in funds facing *No-Load Investors* in column 3 of Table 3 are significantly poorer at anticipating fund flows and adjusting their cash balances accordingly. Institutional investors also exhibit more volatile flow behavior, making anticipation more complicated. Once we control for institutional ownership in column 4, the impact of a one standard-deviation increase in capital commitment increases flow predictability by 0.052 standard deviations. All coefficients are significant at the 1% level.

[Insert Table 3 about here]

Overall, investors in share classes with entry and exit loads are associated with lower fund flow volatility and more predictable flows. Arguably, this should allow portfolio managers to manage cash balances more efficiently. The evidence is robust when we

[12] Results hold when we use a forward-looking approach that regresses prediction ability at $t + 36$ on current capital commitment.

consider front- and back-end share classes separately and after we control for institutional investors and pure no-load funds. These results suggest that the potential conflict of interest between brokers or financial advisors and their clients do not prevent share classes from revealing information about investors' horizon. In particular, front- and back-end investors show stronger long-term capital commitment. Next, we test whether this commitment is related to fund managers' investment strategy.

IV Capital Commitment and Investment Strategy

Even if investors purposefully choose those share classes that better fit their investment horizon, managers may disregard this information because it is redundant or because they lack the adequate incentives to exploit it. Using client-level data on fund share transactions, Johnson (2004) shows that fund managers can make inferences about their clients even in the absence of a load shares. The evidence in Del Guercio and Reuter (2014) suggests that managers broker-sold funds (more likely to use load shares) have weaker incentives to generate alpha than those sold directly (more likely to use no-load shares). Del Guercio and Tkac (2010) show that broker-sold funds cater to a clientele that values nonperformance characteristics. Following these arguments, we should expect no relation between fund investors' capital commitment and fund managers' trading turnover, performance, and portfolio stock selection. That is our null hypothesis.

Under the alternative hypothesis, the percentage of capital commitment influences fund investment horizon, in that managers pursue more long-term strategies by holding stocks longer in a portfolio. Lan, Moneta, and Wermers (2015) and Cremers and Pareek (2016) both show that a longer investment horizon has a positive impact on fund performance. Thus, we will also test the relation between capital commitment and fund performance via the manager's investment horizon.

A Trading Duration

To test the relation between investors' capital commitment and the managers' trading duration, we run the following regression for every fund i and quarter t:

$$Trading\,Duration_{i,t} = \beta_0 + \beta_1\,Capital\,Commitment_{i,t} + \beta_2 Controls_{i,t} + \mu_{i,t} + \epsilon_{i,t}, \quad (2)$$

where *Trading Duration*, introduced by Cremers and Pareek (2016), is based on quarter-end holdings and measures the average length of time (weighted by the size of each stock position) that the fund has held equities in the portfolio over the last five years. *Capital Commitment* is defined as before. We also replace capital commitment with the percentage held by *Back-load* and *Front-load Investors* separately. *Controls* include, besides previous control variables: *Fund Cash, Manager Tenure, Fund Flows,* and *Flow Volatility.* $\mu_{i,t}$ represents time $\times$ objective fixed effects. We standardized the dependent variable and the main independent variables for ease of interpretation. Standard errors are clustered at the fund level. Results are reported in Table 4.

Under the null hypothesis, β_1 is no different from zero. The evidence, however, strongly rejects the null hypothesis. There is a positive correlation between capital commitment and managers' holding horizon. In column 1, a one-standard-deviation increase in capital commitment is associated with 0.050 standard deviations higher trading duration, which is equivalent to a 3.53% (= $(0.05 \times 3.63)/5.14$) increase over the mean holding period. We see also a positive correlation when we separate capital commitment into back- and front-end load assets under management in column 2. All coefficients on these variables are statistically significant at the 1% level. When we control for no-load investors in column 3 or institutional investors in column 4, coefficients on *Capital Commitment* remain positive and significant at the 5% level, and with similar size.

The effect persists even when we control for family-specific unobservables by introducing family fixed effects in Table A3 in the Appendix. All coefficients on *Capital Commitment* are statistically significant at least at the 5% level.[13]

[Insert Table 4 about here]

To test the robustness of these results, we introduce additional controls in Table A5, included in the Appendix. To discourage short-term trading, some mutual fund companies charge a redemption fee within a specified time frame. In column 1 we control for the presence of a redemption fee. The coefficient on *Capital Commitment* remains the same and again significant at the 1% level.

[13] In Table A4 in the Appendix, we corroborate the trading duration findings using alternative horizon proxies like the fund's annual *Turnover Ratio* from CRSP and three duration measures from Lan, Moneta, and Wermers (2015). Generally, a fund that trades frequently tends to have high turnover and a short holding horizon. Consistently, we find a negative and significant relation between the assets managed with entry and exit loads and fund turnover. Regardless of the duration measure used, we document a positive and significant correlation between the manager's trading duration and *Capital Commitment*.

In the second specification, we control, additionally, for the percentage of TNA that comes from *No-Load Investors*. The coefficient on *Capital Commitment* remains positive and of a similar size, and statistically significant at the 5% level. In this second column, the control group is the level share class (typically, C share class). Thus, portfolio managers condition their investment decisions on whether assets under management come from share classes with front- or back-end loads as compared to the level share class where the investment horizon is expected to be shorter. This alleviates concerns that we are capturing unobservable differences across load versus no-load share classes. Additionally, there is no statistically significant relation between assets under management coming from no-load investors and the holding period of the manager.

To control for the possibility that capital commitment is proxying for investor sophistication, we introduce the percentage ownership of institutional investors in the third specification. The coefficient of *Capital Commitment* remains positive and significant at the 5% level. The coefficient on *Institutional Investors* is strong and negatively related to trading duration.

In the fourth column, we control for the manager's incentives by adding the evaluation period in their compensation contract, provided it is based on fund performance as collected by Ma, Tang, and Gomez (2019). The coefficient on *Capital Commitment* increases with the addition of this control variable, and it remains statistically significant at the 1% level. Qualitatively, the results hold unchanged when we control, additionally, for no-load investors (in column 5) and the holdings of institutional investors (in column 6).

B Fund Performance

The evidence in Table 4 suggests a relation between fund managers' investment horizon and the information conveyed by investors' capital commitment. The question we investigate now is whether higher capital commitment is reflected in higher fund performance. The evidence from previous studies strongly suggests that broker-sold funds underperform funds sold directly. In principle, under the null hypothesis, there should be no difference in (under)performance independently of wether investors in broker-sold funds invest mostly in front- or back-load shares versus level-load shares. Under the alternative hypothesis, a higher percentage of front- or back-load shares represents higher investor's capital commitment. Therefore, we first test wether capital commitment enhances the manager's ability to outperform.

We run the following regression:

$$Fund\,Performance\,^{n}_{i,t} = \beta_0 + \beta_1 Capital\,Commitment\,_{i,t} + \beta_2 Controls\,_{i,t} + \mu_{i,t} + \epsilon_{i,t}, \quad (3)$$

where *Fund Performance*$^{n}_{i,t}$ represents the Carhart (1997) four-factor alpha of fund i over the next n months as of period t. We follow Fama and French (1993), and Kamara, Korajczyk, Lou, and Sadka (2016) and calculate the risk-adjusted abnormal returns over the next n periods, with $n \in \{1, 12, 24, 36\}$ months. The four-factor alpha is obtained by regressing buy-and-hold portfolio returns on the corresponding buy-and-hold Carhart (1997) four factors with the same holding horizon. The compounded alphas are then annualized. We use both gross and net returns. The gross monthly returns are computed by adding 1/12 of the expense ratio to the net returns. The controls in this case include *Fund and Family Size, Expense Ratio, Front and Back Load* and *Fund Flows*. $\mu_{i,t}$ represents time $\times$ style fixed effects. We standardized the dependent variable and the main independent variables for ease of interpretation. Standard errors are clustered at the fund level. Results are reported in Table 5.

We reject the null hypothesis: there is a positive and significant relation between *Fund Performance* and *Capital Commitment* both for net and gross fund performance. In column 1, a one-standard deviation in capital commitment is associated with a four-factor annualized alpha 2.2 basis points higher. This increases to 2.7 basis points when we control for institutional investors in specification 2. Expectedly, no-load funds (arguably, more likely to be directly distributed) outperform load funds by 5 basis points annually in specification 3. However, even after controlling for no-load funds, a one-standard deviation increase in capital commitment is associated with 2.8 basis points higher performance. Results are similar for net-of-fee alphas.

[Insert Table 5 about here]

The results in Table 5 show that not all load funds perform equally. Why do funds with higher capital commitment outperform other load funds? Lan, Moneta, and Wermers (2015) and Cremers and Pareek (2016) both find that mutual funds with longer holding periods outperform funds with short trading horizons.[14] Is such outperformance due completely to the fund manager, or is there a role for the supply of capital? Alternatively, when the percentage of committed capital declines, does this undermine the manager's ability to outperform? To answer these questions, we decompose the manager's trading duration into the part predicted by the underlying supply of capital (hence matching the investors' horizon) and the part that is orthogonal to it. This residual should capture managers' holding horizon choice net of the investors' horizon predicted by their share class choice.

To decompose the manager's trading duration of Cremers and Pareek (2016) into the predicted and the residual part with respect to capital commitment, we estimate, for every fund i and every quarter t, the equation:

$$Duration\,Predicted_{\,i,t} = \hat{\beta}_1 Capital\,Commitment_{\,i,t} + \mu_t + \epsilon_{i,t}, \tag{4}$$

where $\hat{\beta}_1$ is the coefficient β_1 estimated in regression (2) with time $\times$ objective fixed effects. Consequently, we obtain the residual value as:

$$Duration\,Residual_{\,i,t} = Trading\,Duration_{\,i,t} - Duration\,Predicted_{\,i,t}. \tag{5}$$

We then run the regression:

$$\begin{aligned} Fund\,Performance^{\,n}_{\,i,t} \quad &= \quad \beta_0 + \beta_1 Duration\,Predicted_{\,i,t} + \beta_2 Duration\,Residual_{\,i,t} + \\ & \quad\quad \beta_3 Controls_{\,i,t} + \mu_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{6}$$

The controls are the same as in (3). We also control for no-load funds. Results are reported in Table 6. We find that gross outperformance is concentrated in the predicted component of the trading duration across the different holding periods. Controlling for fund and family characteristics and time $\times$ fund objective fixed effects, a one-standard-deviation increase in the predicted duration raises the fund's gross four-factor alpha by up to 26 basis points on an annualized basis over the next three years (significant at the 1% level). The component that is orthogonal to the investors' committed capital, on the other side, is much smaller economically (about 5 basis points) and significant only in the next

[14] In Table A6 of the Appendix, we corroborate this finding in our sample using both short- and long-term alphas, and for both gross and net returns.

month but not over longer holding periods. This suggests that the matching of manager and investor investment horizon is key to explain the outperformance associated with longer trading horizons. Conversely, investors can compromise fund managers' ability to outperform if they are impatient and don't reveal their investment horizon.

[Insert Table 6 about here]

To determine what exactly portfolio managers in funds with more capital commitment do differently, we examine the relation between our capital commitment variable and the various sources of systematic risk a portfolio manager exposes a fund to more closely.

We run the following regression:

$$\begin{aligned} Systematic\,Risk\,Loading\,^{f}_{i,t} &= \beta_0 + \beta_1 Capital\,Commitment\,_{i,t} \\ &\quad + Controls\,t_{i,t} + \mu_t + \epsilon_{i,t}, \end{aligned} \tag{7}$$

where *Systematic Risk Loading*$^{f}_{i,t}$ is the winsorized beta exposure of fund i returns at time t to the risk factor f, with $f \in \{MKT, SMB, HML, UMD, PS, PEAD, FIN\}$. We estimate the exposure for a rolling window of 36 months using the value-weighted fund returns regressed on the corresponding factors. The first four factors correspond to the market, size, value, and momentum risk factors of Carhart (1997). *PS* is the traded liquidity factor of Pastor and Stambaugh (2003) and is estimated jointly with the Carhart (1997) factors. The liquidity factor captures exposure to aggregate liquidity, which Pastor and Stambaugh (2003) find to be priced, in that stocks with higher sensitivities to this factor, i.e., higher liquidity betas, have higher average returns[15].

PEAD beta captures a fund's exposure to short-horizon anomalies as introduced by Daniel, Hirshleifer, and Sun (2019), and *FIN* represents a long-horizon factor that exploits more long-horizon mispricing. We estimate this as a three-factor model similar to Daniel, Hirshleifer, and Sun (2019). The long-horizon factor is based on information in managers' decisions to issue or repurchase equity in response to persistent mispricing. The short-horizon earnings surprise factor is motivated by investor inattention and evidence of short-horizon underreaction to earnings. Of particular interest is how funds load on these short- versus long-run mispricing factors as a function of their underlying capital

[15] The traded factor, PS liquidity, is the payoff on the 10–1 portfolio that is long stocks with the highest historical liquidity betas and short stocks with the lowest historical liquidity betas.

commitment. The controls are the same as in equation (6). The factor loadings are estimated using the methodology in Fama and MacBeth (1973).

Results are reported in Table 7. *Capital Commitment* is negatively related to the market (MKT) and size (SMB) factors and positively exposed to aggregate market liquidty (*PS liquidity*) factor. This suggests that funds with more committed capital capitalize on a liquidity premium. Over the cross-section, funds with more committed capital seem to load on the behavioral factors designed to capture long-horizon mispricing (FIN), but not the short-run factor ($PEAD$) consistent with the idea that capital commitment allows managers to exploit slow-moving arbitrage opportunities.

[Insert Table 7 about here]

C Stock Selection

How does capital commitment relate to managers' investment decisions and the type of stocks they select? In particular, do fund managers invest differently when their underlying investors are explicitly providing a long-term capital commitment? Are managers more likely to invest in illiquid stocks if their investors' horizon increases? Is the lack of explicit capital commitment an impediment to exploiting slow-moving trading opportunities that are riskier for funds subject to more volatile flows? To answer these questions, we analyze three broad strategies whose implementation may vary with the amount of committed capital.

Illiquid assets provide a return premium (Amihud (2002)) but are costly to liquidate in the advent of unexpected investor redemptions (fire-sales). We investigate whether managers with more committed capital are less concerned with fire-sale externalities and hold more illiquid stocks to enhance fund performance. We use, as a proxy for the illiquidity of a fund's stock portfolio, the monthly average of the daily Amihud (2002) *Illiquidity* measure.

Funds could also invest in mispriced stocks that are risky to arbitrage because convergence to fundamental value might be slow. Porter (1992) and Hall, Hall, Heaton, and Mankiw (1993) suggest that investors with short time horizons fail to anticipate the rewards from long-term investments such as research and development (R&D). Dow and Gorton (1994) and Goldman and Slezak (2003) argue that the short-term horizons of portfolio managers make them less prone to invest in information acquisition about firms' long-term projects, such as investment in R&D. As a proxy for (long-term) project duration, we use investment-related variables as R&D expenses in the previous year over lagged assets for each stock from Compustat. As an alternative investment variable we also use the KPSS patent data (1926-2010) as obtained from Kogan, Papanikolaou, Seru, and Stoffman (2017). We calculate the value-weighted average of these measures across the fund portfolio holdings to obtain a fund-level quantification of this amount of R&D expense, and call this variable *R&D*. We lag variables one year to reflect that information environment the managers face at the time of their portfolio decisions. We expect higher proportions of committed capital to be positively associated with an investment in these long-term strategies.

Finally, stocks sold off by flow-induced distressed mutual funds are another source of mispricing that is slow to correct (Coval and Stafford (2007)). Arguably, this trading opportunity is riskier for a short-term fund facing frequent redemptions than for a mutual fund whose asset base has a strong capital commitment. We would therefore expect funds with higher capital commitment to invest more in fire-sale stocks to benefit from the correction to fundamental value. Following Edmans, Goldstein, and Jiang (2012), we calculate a flow-induced pressure variable at the stock level by assuming that funds facing outflows sell shares in proportion to their holdings. We calculate the value-weighted average of this measure across holdings to obtain a fund-level variable that we call *Fire-sale Stocks*. We then test whether funds with a higher amount of assets with entry and exit loads invest more in the subsequent quarter in fire-sale stocks.

We run a regression for every fund i and quarter t:

$$Stock\,Characteristic^{\,s}_{i,t+3} = \beta_0 + \beta_1 Capital\,Commitment_{\,i,t} + \beta_2 Controls_{\,i,t} + \alpha_i + \epsilon_{i,t}, \quad (8)$$

where *Stock Characteristic*$^{s}_{i,t+3}$ represents a standardized proxy for the investment strategy $s \in$ {*Illiquidity, R&D, Patents, Fire-sale Stocks*} for fund i next quarter as previously defined. *Capital Commitment* is standardized. The controls are the same as before. α_i denotes fund fixed effects. Standard errors are clustered at the fund level. Results are presented in Table 8.

The higher the fraction of assets in share classes with front- and back-load fees, the more illiquid the holdings of the mutual funds tend to be, as measured by the Amihud (2002) *Illiquidity* variable. In particular, a one-standard deviation in capital commitment is associated with an increase of 0.026 standard deviations, which is equivalent to 9.57% (=(0.026 × 5.08)/1.38)) of the average holdings illiquidity. Funds with a higher fraction of assets in front- or back-end loads also invest more per standard deviation of capital commitment in innovative firms as measured by the R&D intensity or patents within their portfolio choice.

Portfolios with a higher fraction of assets in share classes with front- and back-load fees, are also funds that seem to take advantage of fire-sale stocks. Overall, our results are consistent with our hypothesis that load fee structures provide managers with greater freedom to pursue long-term investment strategies, and invest in more illiquid stocks, and stocks with more innovative investments, and take advantage of arbitrage opportunities where corrections are slow.

[Insert Table 8 about here]

V Robustness Checks and Alternative Interpretations

We have documented a positive correlation between, on one side, managers' portfolio turnover, their investment in illiquid assets, long-term innovative, and slow-correcting misvalued stocks and, on the other side, the amount of committed capital they manage. In this section we check the robustness of our results and explore alternative interpretations. In particular, we implement an empirical strategy to identify the effect of capital commitment on investment strategies. Then, to rule out that capital commitment proxies for investor sophistication or characteristics that managers can infer otherwise, we run two additional robustness tests. The first experiment examines the investors reaction to flows and in particular tests whether committed capital (i.e., front- and back-load shares) is more responsive to performance. For further evidence at the individual investor characteristics, we use the data from a large US discount broker from Barber and Odean (2001) as our second robustness test.

A Regression Discontinuity Design (RDD) based on the WSJ "Category Kings"

Reverse causality is a potential concern in interpretation of our results. Are managers catering to the investment horizon of investors, or rather are investors chasing managers who are more skillful in the long run? Funds may also specialize in certain type of investors (identified with a given distribution channel) and offer only, or predominantly, specific share classes. Another concern is potential omitted variables. Share class choice may actually reflect investor characteristics other than investment horizon (like investor sophistication) that covary simultaneously with our definition of capital commitment (more sophisticated investors may arguably prefer no-load shares) and manager portfolio decisions (more sophisticated investors may be associated with sharper managerial incentives and better monitoring), which would drive spurious results.

To establish a causal relation between capital commitment and fund manager trading behavior, we instrument capital commitment with the flow discontinuity based on the *Wall Street Journal* (WSJ) "Category Kings" ranking exploited by Kaniel and Parham (2017). The *Wall Street Journal* publishes quarterly a list of the top ten performing funds in investment categories in what is known as the "Category Kings" ranking. Kaniel and Parham (2017) use this ranking to implement a regression discontinuity design (RDD) style between the top ten funds as published and the remaining (unpublished) funds.[16] They show a strong discontinuity in capital flows for funds on the WSJ list versus the others.

The WSJ rankings are based on a fund's previous 12-month returns. We hypothesize therefore that a ranked fund should attract more short-term investors who purchase level-load shares through a broker and are unlikely to make a long-term capital commitment. This allows us to exploit exogenous changes in fund capital commitment from the quasi-random assignment around the 10th rank to see whether there is a significant treatment effect of short-horizon capital (lower capital commitment) on the trading behavior of these fund managers as compared to managers of funds in the 11th position, which are almost identical but do not make it in the list.

Figure 3 corroborates the findings of Kaniel and Parham (2017) in that there is a sharp discontinuity in fund net flows (all share classes combined) during the post-publication quarter, showing that the *WSJ* list has a causal effect on mutual fund investor behavior. Figures 4 and 5 further distinguish between the flows coming from the different share class categories. In line with our hypothesis, flow discontinuity seems to come mostly from the level-load share class, where we posit that investors have low capital commitment. Figure 6 shows that the overall proportion of fund TNA allocated to funds with front and back-

[16] The distribution of share classes among funds in the ranking is very similar to the distribution observed in the overall sample: 35% of TNA is in no-load share classes, 20% in level-load, 25% in front-end load, 5% in back-end load, and 15% in other share classes.

end loads (i.e., committed capital) decreases after the publication of the ranking which indicates a significant change in the investor base.[17]

We then explore the causal impact of changes in capital commitment on manager stock selection in the subsequent quarter. We follow an instrumental variable method. Every quarter, we select the subsample of funds listed as the ten top performers in their category denoted "Category Kings." We also include the ten next unpublished best performers per category. These rankings come from Kaniel and Parham (2017). We define *WSJ Discontinuity* as a variable that takes a value of one if the fund is in the published "Category Kings" ranking, and zero otherwise. We also define the variable *WSJ Rank*, which denotes the fund's actual rank.

In the first stage, we instrument the variable *Capital Commitment* with the variable *WSJ Discontinuity*. We also include the variable *WSJ Rank*, the control variables in equation (8), and fund fixed effects. The results are reported in the first column of Table 9. They validate *WSJ Discontinuity* as a relevant instrument. The discontinuity is negative and significantly related (at the 1% level) to the percentage of capital commitment. In the second stage, we examine how the predicted component of *Capital Commitment* from the first stage influences managers' investment decisions in the next quarter. We again include the same control variables and fund fixed effects. Standard errors are clustered at the fund level in both stages. Results are reported in the last four columns of Table 9.

An increase in the fund's predicted capital commitment leads managers to invest significantly more in illiquid securities in the subsequent quarter. We also observe that they increase their investment in innovative firms, as proxied by R&D expenses and patents. We find no evidence on the other hand to support that higher capital commitment increases manager holdings in the next quarter of fire-sale stocks.[18]

We conclude that a shock to capital commitment flows primarily affects fund liquidity

[17]To further corroborate the visual evidence, Table A7 in the Appendix reports the difference in means among several variables between funds ranked 10 and funds ranked 11. There is no statistical difference among inflows coming from capital commitment or no-load share classes but a sizeable difference (significant at the 1% level) in level-load flows.

[18]The exclusion restriction of our instrument can be challenged, as any increase in the predicted capital commitment around the discontinuity is, simultaneously, an increase in fund flows. Hence, we cannot separate the effect of both changes on the manager's strategic decisions. To alleviate this concern, we re-run the RDD test around the *WSJ Discontinuity* restricting the sample to funds with only no-load shares. In this case, any change in the manager's stock selection must be due to changes in fund flows, because the subsample consists of pure no-load funds. Table A8 of the Appendix shows that, in that case, all results vanish. We interpret this as evidence that it is not just the fund flows themselves that drive our results in Table 9, but rather the variation in capital commitment.

management and makes fund managers more willing to invest in arbitrage opportunities that may be slow-moving (Duffie (2010)).

[Insert Table 9 about here]

B Investor sophistication and Capital Commitment

To examine the effect of capital commitment on flow-performance sensitivity, we run a regression as follows for every fund i and every quarter t:

$$\begin{aligned} Fund\,Flows_{\,i,t} \;\; = \;\; & \beta_0 + \beta_1 Commitment\,Dummy_{\,i,t} + \beta_2 Performance\,Rank_{\,i,t} + \\ & \beta_3 High\,Capital\,Commitment_{\,i,t} \times Performance\,Rank_{\,i,t} + \\ & \beta_4 Controls_{\,i,t} + \mu_{i,t} + \epsilon_{i,t}, \end{aligned} \quad (9)$$

where *Fund Flows* is the net growth in fund assets beyond reinvested dividends over the past one year. *Commitment Dummy* takes a value of one (zero) if the fund's percentage of capital commitment lies in the top (bottom) quartile of the sample in month t. Each fund is given a quartile *Performance Rank* based on the fund's gross performance in month t, defined as the fund's gross return net of the median value of the return of all funds within the same investment objective. The controls are the same as in equation (1). $\mu_{i,t}$ represents time and fund fixed effects to control for fund and time-specific unobservables related to fund flows. Standard errors are clustered at the fund level.

Column 1 of Table 10 shows that, unconditionally, investors respond to better performance (higher rank) with inflows. Our object of interest is the coefficient β_3 on the interaction term in equation (9). Funds with more committed capital are significantly less sensitive to short-term performance.

We then break down the flow-performance sensitivity into gross performance terciles (*Low, Mid*, and *High Rank*) in columns 2 through 5 to test whether investors' capital commitment exhibits more or less convexity in the response to fund performance. This also allows us to test whether these investors are more or less sophisticated than the average investor, as in Gil-Bazo and Ruiz-Verdú (2009) and Ferreira, Keswani, Miguel, and Ramos (2012).

It is commonly accepted that bottom-ranked funds exhibit persistence in performance (Carhart (1997)), but no persistence is observed in funds that come out on top in a particular year (Ippolito (1992); Sirri and Tufano (1998); Del Guercio and Tkac (2002)). Therefore, if capital commitment is proxying for investor sophistication, we would expect flows to respond negatively to the low-ranked funds; in other words, we would expect them to flow out of the poorly performing funds and not react to the top-performing ones.

The results fail to support the hypothesis of investor sophistication. Investors in funds with high levels of committed capital react much the same as average investors in the bottom-ranked funds, as the interaction terms between the performance bottom tercile and capital commitment are not statistically significant. In the middle rank do we observe a significant different reaction to performance among funds with higher capital commitment, relative to the top rank where the reaction to performance is less strong among investors with high levels of capital cimmitment.[19]

[Insert Table 10 about here]

C Individual share class choice at the household level

The evidence at the aggregate fund level is consistent with the idea that higher capital commitment is a proxy for a longer investment horizon or more patient capital. We cannot rule out, however, that investors' share class choice relates to other investor characteristics (such as age, wealth, or sex) and not necessarily investment horizon. Also, managers may use available information about personal traits to offer the most suitable share class to a specialized fund clientele, again, independently of their investment horizon. Managers may also infer investors' horizon from other sources (Johnson (2004)). In such cases, share classes would convey no relevant information to managers and should play no role in their portfolio investment decisions.

To address these concerns, we borrow the data used by Barber and Odean (2001). These data include information from a large discount brokerage firm on individual portfolio decisions in accounts opened by 78,000 US households, from January 1991 through December 1996. After we confine the sample to investors with portfolio holdings in at least one mutual fund, the final sample includes the accounts of 27,536 households.

[19] The results remain robust when we control for funds with only no-load shares (*No-load* funds). This suggests that we are not merely capturing structural differences between funds with and without load share classes.

We use these data to estimate a portfolio measure of turnover, following the same methodology as in Barber and Odean (2001). We estimate the turnover of sales and purchases independently. Monthly portfolio turnover is then defined as one-half of sales turnover plus one-half of purchase turnover. To calculate the monthly sales turnover, we match holding positions to sales during the month. The monthly sales turnover is calculated as shares sold times beginning-of-month price per share divided by the total beginning-of-month market value of the household's portfolio. To calculate monthly purchase turnover, we match these positions to purchases during the month. The monthly purchase turnover is calculated as the shares purchased during the month times the end-of-month price per share divided by the total end-of-month market value of the portfolio.[20]

We run, for each quarter t and household j, the regression:

$$PortfolioTurnover_{j,t} = \beta_0 + \beta_1^s H_{j,t}^s + \beta_2 Controls_{j,t} + \mu_{j,t} + \rho_{j,t} + \epsilon_{i,t},$$

where $H_{j,t}^s$ represents the percentage of investor j holdings invested in, respectively, share class s={*Front-Load, Back-Load, Level-Load, No-Load*} in quarter t. The object of interest is the coefficient β_1^s for each share class s. We control for several household characteristics potentially correlated with portfolio turnover: the investor's marginal tax rate (*Tax*), *Wealth*, and indicator variables for sex (*Male*), age (*Under 45*), marital status (*Married*), and whether the investor is a *Homeowner*. The data identify the household's investment style (conservative, income, growth, or speculation) and financial knowledge (extensive, good, limited, or none). We include month $\times$ style ($\mu_{j,t}$) and month $\times$ knowledge ($\rho_{j,t}$) dummies. The independent variables are standardized. Standard errors are clustered at the investor level. The results are shown in Table 11.

[Insert Table 11 about here]

Portfolio turnover is lower among households with a higher proportion of holdings invested in mutual fund front-end load shares. In particular, a one-standard-deviation increase in the proportion of front-end load shares reduces portfolio turnover by 0.55%. In economic terms, this reduction represents around 22% of the average turnover (2.5%).

[20] If more shares were sold than were held at the beginning of the month (an investor might have purchased additional shares after the beginning of the month), we assume the entire beginning-of-month position in that security was sold. Similarly, if more shares were purchased during the month than were held in the position statement at month-end, we assume that the entire position was purchased during the month. Thus, the estimated turnover cannot exceed 100% in a month.

On the other side. All coefficients are significant at the 1% level. Wealthier investors and investors with higher marginal tax rates also tend to show higher portfolio turnover.

These results support, at the household level, our hypothesis that investment in front-end load shares tends to be associated with lower trading frequency, while investment in level-load shares and no-load shares is associated with higher trading frequency. This is true even after controlling for several personal investor characteristics (presumably known to the manager). In other words, share class choice reveals additional information to the manager about likely investor portfolio turnover and, potentially, their capital commitment.

The results in Table 11 suggest that share class choice is a good predictor of the household's overall trade frequency. In the Appendix, we examine the turnover of the portfolios of individual investors in our sample. Following the same methodology as in Barber and Odean (2001), we estimate the monthly turnover of the holdings of 27,536 households in 1,001 mutual funds from January 1991 through December 1996. We then regress turnover of fund i shares from investor j at time t against a dummy variable $I^s_{i,j,t}$ takes a value of 1 if fund i of investor j in month t is, respectively, in share class s=$\{$*Front-Load, Back-Load, Level-Load, No-Load*$\}$, zero otherwise. We control for fund characteristics like *Fund Size, Fund Age, Fund Fee,* and dummy variables for *Index Funds* and *Equity Funds.* We add household fixed effects ($\mu_{j,t}$) to control for unobservable characteristics at the individual investor level. Standard errors are clustered at the investor level.

Results are presented in Table A9 of the Appendix. The turnover of front-end fund shares is, on average, 0.07% lower than the average turnover in other fund classes, while the level-load and no-load fund share turnovers are 0.18% and 0.07% higher, respectively. Given that the average turnover of these securities is 0.3%, these measures are economically meaningful. All coefficients are statistically significant at the 1% level and robust after controlling for several fund characteristics.

These results are consistent with our hypothesis that share class choice reveals investors' capital commitment, here measured by the underlying investor turnover of both their overall portfolios and their mutual fund investments. This evidence is robust after controlling for investor and fund characteristics. This supports our conjecture that share class choice reveals additional information about the investor's capital commitment beyond what a manager can potentially gather from investor characteristics.

D Alternative signaling mechanisms: Prospectus disclosure

Our data show that the percentage of no-load shares has been steadily increasing during our sample period. The decoupling of financial advice and investment together with a higher demand for passive (and cheaper) financial assets like exchange traded funds (ETFs) in recent years has put strong pressure on mutual fund front- and back-end load fees. Back-end load shares have practically disappeared while the proportion of level-load shares, although still sizeable, exhibits a declining trend since 2005.

Given these trends, if information revealed through investors' choice among load shares is truly valuable to portfolio managers, we expect that funds will look for alternative ways to infer investor horizons or attract investors with similar horizons. Is there any evidence of alternative signaling mechanisms beyond fee structures? This is the question we address in this section.

Mutual funds can communicate their investment strategy in their prospectus and semi annual reports. If a fund family offers no-load shares, arguably losing a valuable channel of information about investors' capital commitment, we would expect its funds to be more explicit in the prospectus about the manager's investment horizon relative to funds in families without no-load shares.

We download the prospectus reports (Form 485 BPOS) from Edgar and count the number of times a fund explicitly mentions the word "long-term" as a signal of its investment horizon. In Table 12, we regress the number of times the word "long-term" appears in the fund prospectus on an indicator variable, *No-Load Family*, that equals one for funds in mutual fund families with a no-load distribution channel, zero otherwise. We control for total word count as our key-word could simply mechanically appear more frequently in longer prospectuses.

We find that funds in no-load families use the word "long-term" more frequently. In fact, they mention it between four to six times more than funds in a family without no-load classes. This is consistent with the idea that a fund family recognizes the importance of signaling the investment horizon of a fund, particularly when the introduction of no-load shares makes the share class choice of investors less informative about their investment horizon. In other words, they recognize the importance of matching capital horizon to the underlying investor's horizon and they present the information accordingly.

[Insert Table 12 about here]

In the Appendix, we test an alternative signal that funds could use to inform investors about their investment horizon, which could be establishment of a redemption fee. The redemption fee is charged when investors withdraw money from a fund. This fee does not go back into the pockets of the fund's advisor but rather into the fund itself. Moreover, unlike contingent deferred sales charges, redemption fees typically apply only in short, specific periods, commonly 30, 180, or 365 days (although some redemption fees exist for up to five years). Charges are waived after the stated time has passed. These fees are typically imposed to discourage market-timers, whose quick movements into and out of funds can be disruptive.

We controlled for the presence of a redemption fee in Table A5 to check the robustness of *Capital Commitment* on the investment horizon of portfolio managers. Now, we want to test explicitly whether funds use such a fee as a retention mechanism when the fund has less capital commitment. In Table A10 we find support for this prediction. There is evidence of a negative relation between *Capital Commitment* and the probability that a fund has a redemption fee.

VI Conclusion

We have argued that mutual fund managers can extract valuable information on their investment from investors choices among different sale charge fee structures. Investors who choose funds with sizeable front- or back-end loads reveal a rational commitment to hold their positions longer than investors who choose level-load shares or no-load shares.

We examine whether investors' choice among sale charge fees has implications for mutual funds, investors themselves, and the behavior of portfolio managers. We define capital commitment as the proportion of a fund's TNA invested in funds in front- or back-end load share classes. We find that the lack of explicit capital commitment affects fund trading horizon, stock selection, and in turn overall fund performance. The information embedded in investor load fee choice helps managers deliver performance by efficiently matching their investment choices to the underlying investment horizon of the retail investor.

Our results show evidence that mutual funds with more committed capital hold stocks for longer periods, hold more iliquid stocks, and invest in long-term oriented firms. These funds also take more advantage of mispriced stocks where convergence to fundamental value is slow.

We document an important role for mutual fund charges in stabilizing flows, matching investment horizon, and contributing to overall long-term performance. These concerns are shared by the financial regulator in terms of protecting mutual fund shareholders from volatile capital flows as well as preserving the liquidity needs of funds. Since 2016, the SEC has allowed the use of *swing or dual pricing*, defined as "the process of adjusting the fund's net asset value (NAV) per share to effectively pass on the costs stemming from shareholder purchase or redemption activity to the shareholders associated with that activity" (amendments to rule 22c-1 of the Investment Company Act). Future research could test whether this regulation might replace investor share class choice as a stabilizing mechanism.

There is a common view that disintermediation benefits investors unconditionally; that is, it is cost-saving. Our results suggest rather that a broker distribution channel provides useful information about investors' capital commitment. This helps managers to make portfolio decisions that generate value for fund investors.

References

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik, 2009, Role of managerial incentives and discretion in hedge fund performance, *Journal of Finance* 64, 2221–2256.

Agarwal, Vikas, Rahul Vashishtha, and Mohan Venkatachalam, 2018, Mutual fund transparency and corporate myopia, *The Review of Financial Studies* 31, 1966–2003.

Agarwal, Vikas, and Haibei Zhao, 2020, Interfund lending in mutual fund families: Role of internal capital markets, *Review of Financial Studies, forthcoming.*

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effect, *Journal of Financial Markets* 5, 31 – 56.

Aragon, George O., 2007, Share restrictions and asset pricing: Evidence from the hedge fund industry, *Journal of Financial Economics* 83, 33–58.

Barber, Brad M, and Terrance Odean, 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *The Quarterly Journal of Economics* 116, 261–292.

Barber, B. M., T. Odean, and L. Zheng, 2005, Out of sight, out of mind: The effects of expenses on mutual fund flows, *Journal of Business* 78.

Bergstresser, Daniel, John M. R. Chalmers, and Peter Tufano, 2009, Assessing the costs and benefits of brokers in the mutual fund industry, *Review of Financial Studies* 22, 4129–4156.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Chalmers, John, and Jonathan Reuter, 2020, Is conflicted investment advice better than no advice?, Discussion Paper NBER, Journal of Financial Economics, forthcoming.

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis, 2001, The stock market valuation of research and development expenditures, *The Journal of Finance* 56, 2431–2456.

Chernenko, Sergey, and Adi Sunderam, 2016, Liquidity transformation in asset management: Evidence from the cash holdings of mutual funds, *Working Paper*.

Chordia, Tarun, 1996, The structure of mutual fund charges, *Journal of Financial Economics* 41, 3 – 39.

Christoffersen, Susan E. K., Richard Evans, and David K. Musto, 2013, What do consumers' fund flows maximize? evidence from their brokers' incentives, *The Journal of Finance* 68, 201–235.

Cohen, Lauren, Karl Diether, and Christopher Malloy, 2013, "misvaluing innovation", *The Review of Financial Studies* 26, 635–666.

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Cremers, Martijn, and Ankur Pareek, 2016, Patient capital outperformance: The investment skill of high active share managers who trade infrequently, *Journal of Financial Economics* 122, 288–306.

Daniel, Kent, David Hirshleifer, and Lin Sun, 2019, Short- and long-horizon behavioral factors, *Forthcoming the Review of Financial Studies*.

Del Guercio, Diane, and Jonathan Reuter, 2014, Mutual fund performance and the incentive to generate alpha, *The Journal of Finance* 69, 1673–1704.

Del Guercio, Diane, and Paula Tkac, 2002, The determinants of the flow of funds of managed portfolios: Mutual funds vs. pension funds, *Journal of Financial and Quantitative Analysis* 37, 523–557.

Del Guercio, Diane, Jonathan Reuter, and Paula Tkac, 2010, Broker incentives and mutual fund market segmentation, Working Paper - NBER.

Dow, James, and Gary Gorton, 1994, Arbitrage chains, *Journal of Finance* 49, 819–49.

Duffie, Darrell, 2010, Presidential address: Asset price dynamics with slow-moving capital, *Journal of Finance* 65, 1237–1267.

Eberhart, Allan C., William F. Maxwell, and Akhtar R. Siddique, 2004, An examination of long-term abnormal stock returns and operating performance following r&d increases, *The Journal of Finance* 59, 623–650.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: The impact of prices on takeovers, *The Journal of Finance* 67, 933–971.

Fama, Eugene, and Kenneth French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Ferreira, Miguel, Aneel Keswani, Antonio F. Miguel, and Sofia Ramos, 2012, The flow-performance relationship around the world, *Journal of Banking and Finance* 36, 1759–1780.

Giannetti, Mariassunta, and Bige Kahraman, 2018, Open-End Organizational Structures and Limits to Arbitrage, *Review of Financial Studies* 31, 773–810.

Gil-Bazo, Javier, and Pablo Ruiz-Verdú, 2009, The relation between price and performance in the mutual fund industry, *The Journal of Finance* 64, 2153–2183.

Goldman, Eitan, and Steve L. Slezak, 2003, Delegated portfolio management and rational prolonged mispricing, *The Journal of Finance* 58, 283–311.

Hall, Bronwyn H., Robert E. Hall, John Heaton, and N. Gregory Mankiw, 1993, The value and performance of u.s. corporations, *Brookings Papers on Economic Activity* 1993, 1–49.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2013, Innovative efficiency and stock returns, *Journal of Financial Economics* 107, 632–654.

Ippolito, R., 1992, Consumer reaction to measures of poor quality: evidence from the mutual fund industry., *Journal of Law and Economics* 35, 45–70.

Johnson, W., T., 2004, Predictable investment horizons and wealth transfers among mutual fund shareholders, *The Journal of Finance* 59, 1979–2012.

Kamara, Avraham, Robert A. Korajczyk, Xiaoxia Lou, and Ronnie Sadka, 2016, Horizon pricing, *Journal of Financial and Quantitative Analysis* 51, 1769–1793.

Kaniel, Ron, and Robert Parham, 2017, Wsj category kings – the impact of media attention on consumer and mutual fund investment decisions, *Journal of Financial Economics* 123, 337–356.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017, Technological innovation, resource allocation, and growth, *The Quarterly Journal of Economics* 132, 665–712.

Lan, Chunhua, Fabio Moneta, and Russ Wermers, 2015, Mutual fund investment horizon and performance, CFR Working Papers 15-06.

Lauren, Cohen, and Lou Dong, 2012, Complicated firms, *Journal of Financial Economics* 104, 383 – 400.

Lev, Baruch, and Theodore Sougiannis, 1996, The capitalization, amortization, and value-relevance of r&d, *Journal of Accounting and Economics* 21, 107 – 138.

Ma, Linlin, Yuehua Tang, and Juan-Pedro Gomez, 2019, Portfolio manager compensation in the u.s. mutual fund industry, *Journal of Finance* 74, 587–638.

Nanda, Vikram, Z. Jay Wang, and Lu Zheng, 2009, The abcs of mutual funds: On the introduction of multiple share classes, *Journal of Financial Intermediation* 18, 329–361.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Pastor, Lubos, and Robert F. Stambaugh, 2003, The stock market valuation of research and development expenditures, *Journal of Political Economy* 111, 642–685.

Porter, Michael E., 1992, Capital choices: Changing the way america invests in industry, *Journal of Applied Corporate Finance* 5, 4–16.

Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589–1622.

Stein, Jeremy C., 2005, Why are most funds open-end? competition and the limits of arbitrage, *Quarterly Journal of Economics* 120, 247–272.

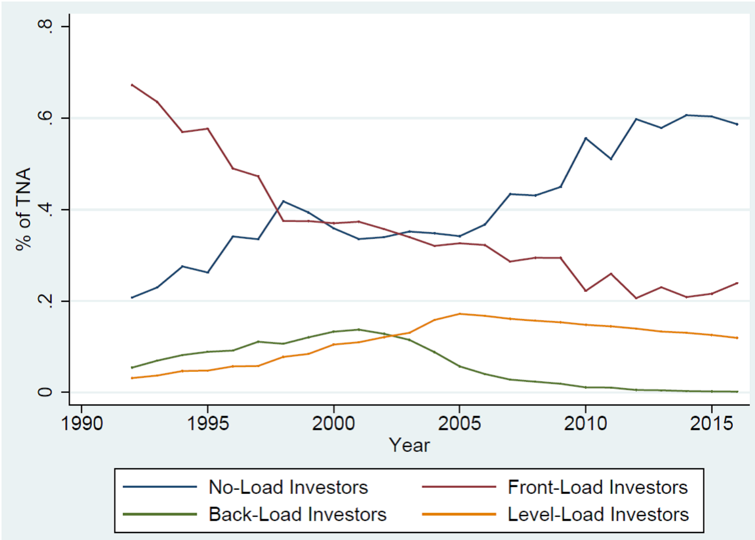

Figure 1: Fraction of Total Net Assets (TNA) by Share Class
The figure shows the percentage of investor TNA in each share class and year across all funds in the sample. We follow the Investment Company Institute (ICI) share classification system and identify four share classes. Load shares are all retail. No-load shares can be retail or institutional (including class R).

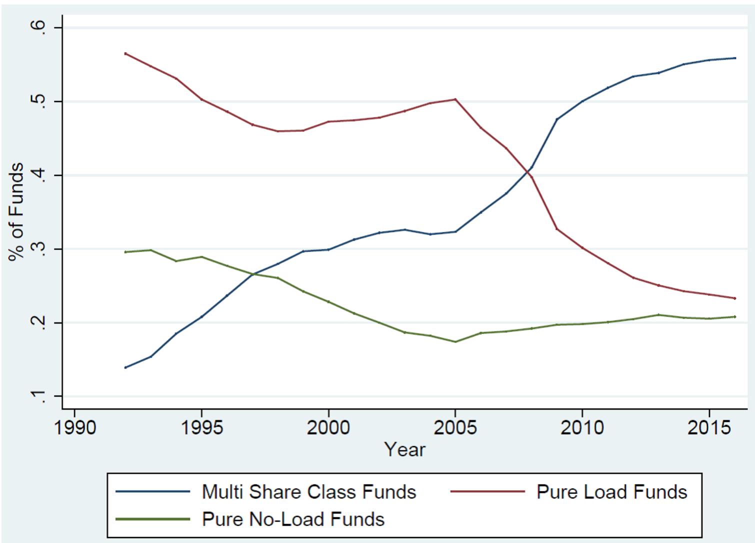

Figure 2: Fraction of Funds by Distribution Policy
The figure shows the percentage of funds in each type of distribution policy and year in our sample. We classify a fund as *Multi-class* if the fund offers load and no-load class options. *Pure load* (alternatively, *Pure no-load*) funds offer only load (alternatively, no-load) shares. For the definition of load and no-load share class, see Figure 1.

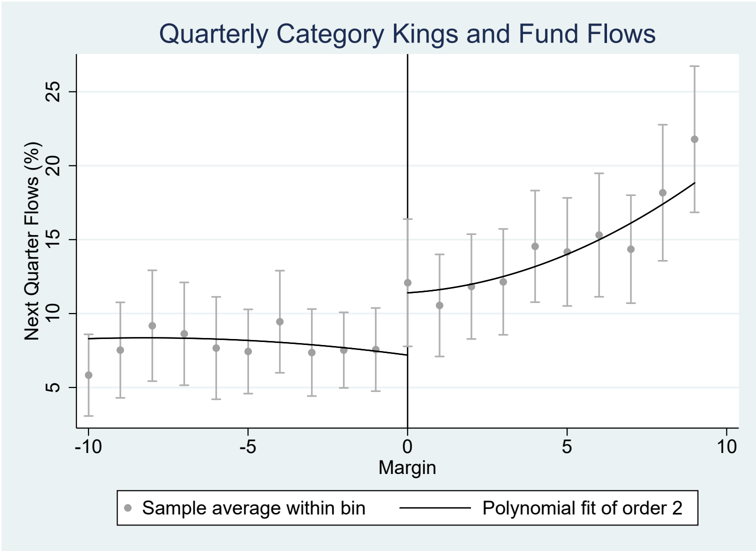

Figure 3: RDD Analysis of Post-Publication Fund Flows by Rank. All Share Classes. Every quarter, funds in each category are sorted into ten ranks published by WSJ the "Category Kings" (bins 0 through 10) and ten consecutive unpublished ranks (bins 0 through -10) based on their performance over the last 12 months. The vertical axis represents the fund net flows (as a percentage of TNA) regardless of share class over the quarter following the publication fo ranks.

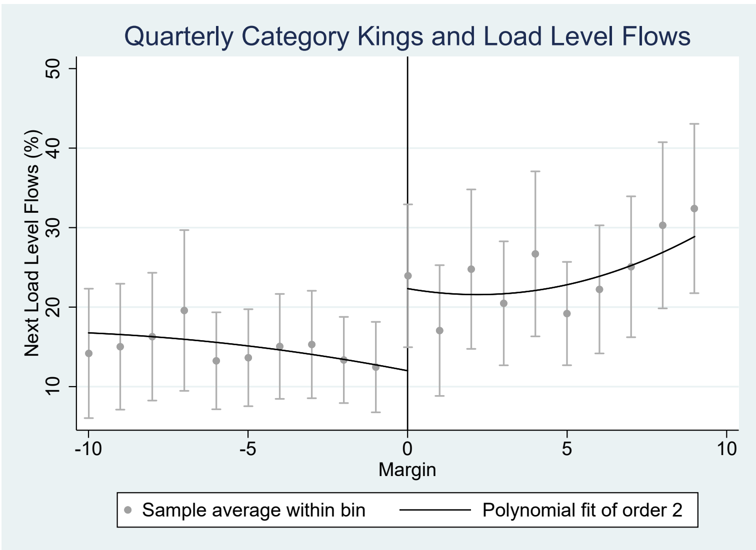

Figure 4: RDD Analysis of Post-Publication Fund Flows by Rank. Only Level-Load Shares. Every quarter, funds in each category are sorted into ten ranks published by WSJ the "Category Kings" (bins 0 through 10) and ten consecutive unpublished ranks (bins 0 through -10) based on their performance over the last 12 months. The vertical axis represents the fund net flows (as a percentage of TNA) corresponding only to level-load class shares over the quarter following the publication of ranks.

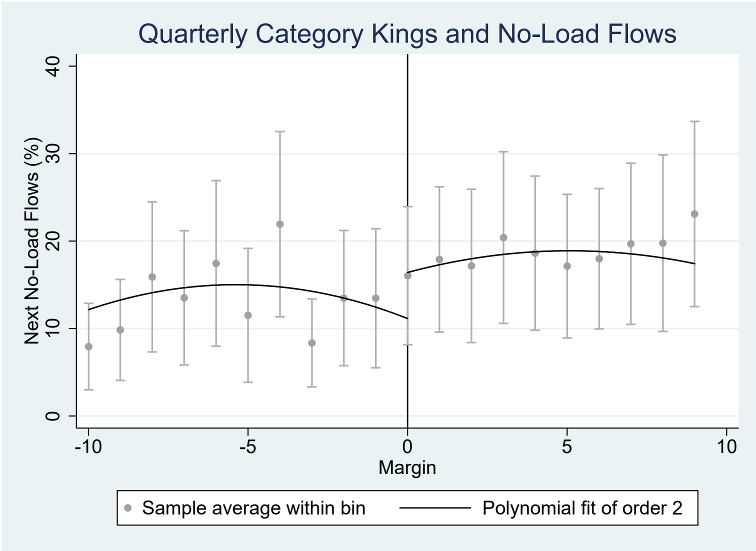

Figure 5: RDD Analysis of Post-Publication Fund Flows by Rank. Only No-load Shares. Every quarter, funds in each category are sorted into ten ranks published by WSJ the "Category Kings" (bins 0 through 10) and ten consecutive unpublished ranks (bins 0 through -10) based on their performance over the last 12 months. The vertical axis represents the fund net flows (as a percentage of TNA) corresponding only to No-load shares over the quarter following the raking publication.

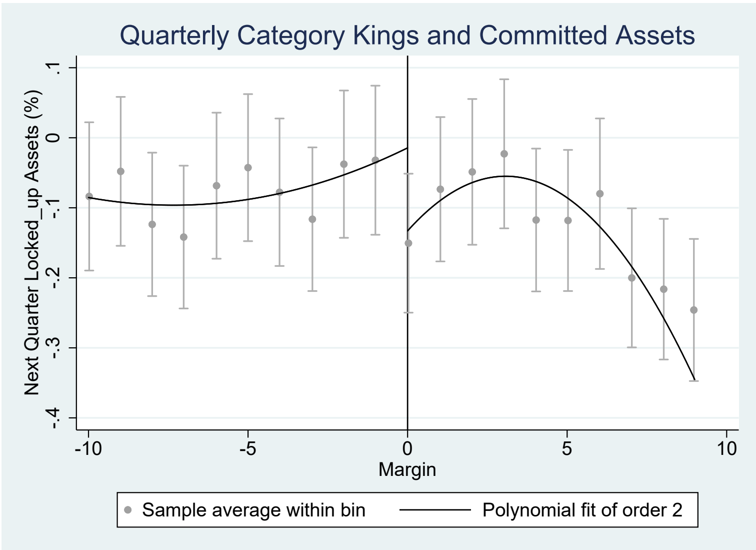

Figure 6: RDD Analysis of Post-Publication Fund TNA by Rank. Only Capital Commitment. Every quarter, funds in each category are sorted into ten ranks published by WSJ the "Category Kings" (bins 0 through 10) and ten consecutive unpublished ranks (bins 0 through -10) based on their performance over the last 12 months. The vertical axis represents the fund TNA corresponding only to shares with entry or exit load fees the quarter following the raking publication.

Table 1: Summary Statistics

This table reports mean, standard deviation, 25th-percentile, median, and 75th-percentile of mutual fund share classes in Panel A, and fund characteristics in Panel B. The definition of all variables is provided in Table A1 of the Appendix.

	Panel A: Total Net Assets by Share Class				
	mean	sd	p25	p50	p75
Capital Commitment	31.70	39.56	0.00	1.94	72.90
Front Investors	26.24	34.95	0.00	0.84	52.32
Back Investors	5.46	14.99	0.00	0.00	0.85
Level Investors	19.46	33.08	0.00	1.70	19.97
No Load Investors	38.11	44.10	0.00	5.42	95.95

	Panel B: Fund and Family Characteristics				
	mean	sd	p25	p50	p75
Fund TNA ($ million)	1948.01	6177.07	53.17	267.34	1287.11
Fund Size (log $ million)	5.49	2.32	3.97	5.59	7.16
Family Size (log $ million)	8.97	2.83	7.36	9.43	11.12
Family Funds (#)	161.37	212.43	13.00	74.00	240.00
Fund Age (years)	12.58	13.06	4.08	8.92	16.00
Expense Ratio (% per year)	1.28	0.49	0.98	1.23	1.53
Turnover Ratio (% per year)	89.39	98.68	33.00	64.00	111.00
Fund Cash(%)	4.52	7.09	0.75	2.66	5.70
Raw Return (% per month)	0.89	5.05	-1.49	1.18	3.72
Fund Performance (% annualized)	0.18	2.14	-0.79	0.13	1.07
Manager Tenure (log years)	1.76	0.72	1.23	1.78	2.24
Manager Evaluation Period (years)	3.20	0.74	3.00	3.00	3.00
Trading Duration (quarters)	5.14	3.63	2.46	4.16	7.01
Iliquidity (ratio)	1.38	5.08	0.01	0.07	0.37
Fund Flows(% per month)	2.16	12.13	-2.56	0.72	4.63
Total Flow Volatility (%)	3.51	6.30	0.64	1.50	3.49
Flow Prediction (%)	6.80	10.76	0.29	2.40	8.59
Front Load (%)	3.97	2.42	0.00	5.25	5.75
Back Load (%)	2.20	2.08	0.00	2.00	5.00
Institutional Investors (%)	21.86	35.57	0.00	0.00	31.26
Redemption Fee (%)	17.33	37.85	0.00	0.00	0.00

Table 2: Flow Stability and Capital Commitment

The table presents the results of regressing the fund's total flow volatility on the percentage of the fund's TNA in different share classes and fund characteristics. The dependent variables is the standard deviation of monthly inflows and outflows in the following 24 months. *No-Load, Back, Front*, and *Institutional Investors* represent the percentage of fund TNA in the corresponding share classes. *Capital Commitment* is the percentage of fund TNA in share classes with either front or back load fee. We standardize the dependent variable and the main explanatory variables. The control variables are defined in Table A1 of the Appendix. Standard errors are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Fund Flow Volatility			
	(1)	(2)	(3)	(4)
Capital Commitment	-0.118***		-0.095***	-0.127***
	(-6.79)		(-5.64)	(-6.48)
Back Investors		-0.043***		
		(-3.09)		
Front Investors		-0.105***		
		(-6.72)		
No Load Investors			0.050**	
			(2.53)	
Institutional Investors				-0.034**
				(-2.07)
Size (log(TNA))	-0.147***	-0.147***	-0.149***	-0.147***
	(-14.36)	(-14.23)	(-14.37)	(-14.28)
Family Size	-0.017	-0.017	-0.013	-0.022
	(-1.19)	(-1.19)	(-0.94)	(-1.41)
Family Funds (log)	0.053**	0.052**	0.046**	0.060***
	(2.50)	(2.50)	(2.21)	(2.65)
Expense Ratio	0.023	0.022	0.046	0.005
	(0.67)	(0.56)	(1.21)	(0.15)
Load Fee	-0.001	-0.001	-0.000	-0.000
	(-0.15)	(-0.15)	(-0.07)	(-0.06)
Fund Age (log)	0.074***	0.074***	0.077***	0.071***
	(3.90)	(3.86)	(3.97)	(3.72)
Time x Style FE	Y	Y	Y	Y
Observations	77041	77041	77041	77041
Adjusted r^2	0.133	0.133	0.135	0.134

Table 3: Liquidity Management and Capital Commitment

The table presents the results of regressing *Fund Flows Prediction* on the percentage of the fund's TNA in different share classes and fund characteristics. The dependent variable is the R-squared from regressing fund net flows on past cash holdings using 36 months of observations. *No-Load, Back, Front*, and *Institutional Investors* represent the percentage of fund TNA in the corresponding share classes. *Capital Commitment* is the percentage of fund TNA in share classes with either front or back load fee. We standardize the dependent variable and the main explanatory variables. The control variables are defined in Table A1 of the Appendix. Standard errors are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Fund Flows Prediction			
	(1)	(2)	(3)	(4)
Capital Commitment	0.064***		0.035**	0.052***
	(4.47)		(2.26)	(3.49)
Back Investors		0.046**		
		(2.57)		
Front Investors		0.052***		
		(3.97)		
No Load Investors			-0.069***	
			(-4.93)	
Institutional Investors				-0.041***
				(-3.28)
Size (log(TNA))	0.084***	0.083***	0.085***	0.084***
	(11.04)	(10.85)	(11.23)	(11.01)
Family Size	0.009	0.009	0.002	0.002
	(0.79)	(0.72)	(0.19)	(0.20)
Family Funds (log)	-0.021	-0.022	-0.010	-0.011
	(-1.32)	(-1.39)	(-0.58)	(-0.63)
Expense Ratio	0.080**	0.066*	0.046	0.054
	(2.27)	(1.80)	(1.27)	(1.48)
Load Fee	0.010	0.010	0.010	0.011
	(1.50)	(1.51)	(1.40)	(1.54)
Fund Age (log)	-0.070***	-0.068***	-0.074***	-0.077***
	(-2.86)	(-2.74)	(-3.04)	(-3.10)
Fund Flows	0.000	0.000	0.000	0.000
	(0.29)	(0.39)	(0.40)	(0.15)
Time x Style FE	Y	Y	Y	Y
Observations	57584	57584	57584	57584
Adjusted r^2	0.036	0.036	0.037	0.036

Table 4: Trading Duration and Capital Commitment

The table reports the results of regressing the manager's *Trading Duration* on the percentage of the fund's TNA in different share classes and fund characteristics. *Trading Duration*, introduced in Cremers and Pareek (2016), is based on quarter-end holdings and measures the weighted-average (weighted by the size of each stock position) length of time that the fund has held equities in the portfolio over the last five years. *No-Load, Back, Front*, and *Institutional Investors* represent the percentage of fund TNA in the corresponding share classes. *Capital Commitment* is the percentage of fund TNA in share classes with either front or back load fee. We standardize the dependent variable and the main explanatory variables. The control variables are defined in Table A1 of the Appendix. Standard errors are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Trading Duration			
	(1)	(2)	(3)	(4)
Capital Commitment	0.050***		0.043**	0.040**
	(2.96)		(2.18)	(2.23)
Back Investors		0.030**		
		(2.34)		
Front Investors		0.042***		
		(2.72)		
No Load Investors			-0.015	
			(-0.74)	
Institutional Investors				-0.043**
				(-2.54)
Size (log(TNA))	0.115***	0.114***	0.115***	0.114***
	(13.18)	(13.04)	(13.18)	(13.11)
Family Size	0.019	0.018	0.018	0.015
	(1.39)	(1.33)	(1.30)	(1.09)
Family Funds (log)	-0.123***	-0.124***	-0.121***	-0.116***
	(-5.55)	(-5.57)	(-5.43)	(-5.18)
Expense Ratio	-0.238***	-0.249***	-0.245***	-0.258***
	(-6.32)	(-6.14)	(-6.40)	(-6.86)
Load Fee	-0.004	-0.004	-0.004	-0.002
	(-0.53)	(-0.53)	(-0.54)	(-0.31)
Fund Cash	0.000	0.000	0.000	-0.000
	(0.03)	(0.09)	(0.01)	(-0.04)
Fund Flows	-0.003***	-0.003***	-0.003***	-0.003***
	(-9.08)	(-9.12)	(-9.07)	(-9.24)
Time x Style FE	Y	Y	Y	Y
Observations	122481	122481	122481	122481
Adjusted r^2	0.254	0.254	0.254	0.255

Table 5: Fund Performance and Capital Commitment

The table reports the results of regressing the *Fund Performance* on the percentage of the fund's TNA in different share classes and fund characteristics. Fund performance corresponds to the alpha obtained from the Carhart (1997) four factors model. We use both gross (before fee) and net (after fee) returns. *Capital Commitment* is the percentage of fund TNA in share classes with either front or back load fee. *Institutional Investors* represent the percentage of fund TNA in the corresponding share classes. *Noload Fund* is an indicator variable for funds without load share classes. We standardize the dependent variable and the main explanatory variables. The control variables are defined in Table A1 of the Appendix. Standard errors are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Fund Performance (Gross Returns)			Fund Performance (Net Returns)		
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Commitment	0.022**	0.027***	0.028***	0.025**	0.029***	0.030***
	(2.29)	(2.60)	(2.70)	(2.53)	(2.79)	(2.88)
Institutional Investors		0.013*	0.015*		0.012	0.014*
		(1.74)	(1.90)		(1.63)	(1.78)
Noload Fund			0.050**			0.048**
			(2.20)			(2.06)
Size (log(TNA))	-0.027***	-0.027***	-0.026***	-0.027***	-0.027***	-0.026***
	(-5.77)	(-5.53)	(-5.46)	(-5.86)	(-5.62)	(-5.55)
Family Size	0.009**	0.009**	0.009**	0.011***	0.011***	0.010***
	(2.47)	(2.45)	(2.35)	(2.85)	(2.83)	(2.73)
Expense Ratio	-0.098***	-0.091***	-0.085***	-0.180***	-0.174***	-0.168***
	(-4.11)	(-3.71)	(-3.41)	(-7.22)	(-6.77)	(-6.38)
Front Load	-0.761**	-0.947***	-0.740*	-0.787**	-0.960***	-0.760**
	(-2.22)	(-2.61)	(-1.94)	(-2.31)	(-2.65)	(-1.99)
Back Load	-0.077	-0.102	0.070	-0.026	-0.049	0.117
	(-0.20)	(-0.27)	(0.18)	(-0.07)	(-0.13)	(0.31)
Fund Cash	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*
	(1.66)	(1.70)	(1.74)	(1.73)	(1.78)	(1.81)
Fund Flows	0.056***	0.056***	0.056***	0.056***	0.056***	0.056***
	(25.67)	(25.69)	(25.70)	(25.67)	(25.68)	(25.69)
Time x Style FE	Y	Y	Y	Y	Y	Y
Observations	135161	135161	135161	135161	135161	135161
Adjusted r^2	0.215	0.215	0.215	0.215	0.215	0.215

Table 6: Fund Performance and Capital Commitment

The table reports the results of regressing the *Fund Performance* on fund characteristics. Fund performance corresponds to the alpha obtained by regressing buy-and-hold portfolio returns on the corresponding buy-and-hold Carhart (1997) four factors with the same holding horizon. The compounded alphas are then annualized. We decompose the (standardized) trading duration of Cremers and Pareek (2016) into the part predicted by the variable *Capital Commitment* and the part that is orthogonal to it. The residual should capture the manager holding horizon choice, net of the capital commitment observed among investors, and the predicted holding period captures the holding horizon of fund managers due to investors' supply of long-term capital. *Capital Commitment* is the percentage of fund TNA in share classes with either front or back load fee. *Institutional Investors* represent the percentage of fund TNA in the corresponding share classes. *Noload Fund* is an indicator variable for funds without load share classes. The control variables are defined in Table A1 of the Appendix. The constant term is included but not reported. The t-statistics adjusted for serial correlation using Newey and West (1987) are reported in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Fund Performance			
	t	t+12	t+24	t+36
Duration Predicted	0.377***	0.138**	0.138*	0.262***
	(4.08)	(2.08)	(1.92)	(3.44)
Duration Residual	0.053***	-0.007	-0.008	0.008
	(6.03)	(-1.23)	(-1.48)	(1.33)
Noload Fund	0.013	-0.038	-0.042	-0.041
	(0.41)	(-1.53)	(-1.56)	(-1.46)
Institutional Investors	0.022**	0.013**	0.020***	0.016**
	(2.49)	(2.05)	(3.10)	(2.39)
Size (log(TNA))	-0.076***	0.014	0.023**	0.022**
	(-6.20)	(1.56)	(2.39)	(2.16)
Family Size	0.032***	0.008*	0.005	0.005
	(4.51)	(1.74)	(0.87)	(0.85)
Expense Ratio	0.010	0.129***	0.160***	0.179***
	(0.29)	(5.11)	(5.79)	(5.89)
Front Load	0.115	-1.399***	-1.405***	-1.378***
	(0.28)	(-4.66)	(-4.44)	(-4.39)
Back Load	0.340	-1.581***	-1.832***	-1.662***
	(0.82)	(-5.23)	(-5.58)	(-4.84)
Fund Cash	0.001	0.005***	0.007***	0.007***
	(0.57)	(5.44)	(5.94)	(6.44)
Fund Flows	0.054***	0.010***	0.008***	0.006***
	(23.24)	(15.72)	(16.18)	(12.41)
Time x Style FE	Y	Y	Y	Y
Observations	103760	103907	103907	103907
Adjusted r^2	0.220	0.228	0.265	0.247

Table 7: Systematic Risk Exposure and Capital Commitment

The table reports the results of regressing the beta exposure of each fund and period with respect to a set of risk factors on *Capital Commitment* and fund characteristics. We run the regressions: $Systematic\,Risk\,Loading^{f}_{i,t} = \beta_0 + \beta_1 Capital\,Commitment_{i,t} + Controls\,t_{i,t} + \mu_t + \epsilon_{i,t}$ where $Systematic\ Risk\ Loading^{f}_{i,t}$ is the beta exposure of fund i returns at time t to the risk factor f, with $f \in \{MKT, SMB, HML, UMD, PS, PEAD, FIN\}$. We estimate the exposure based on a rolling window of 36 months using the value-weighted fund returns regressed on the corresponding factors. The first four factors correspond to market, size, value, and momentum risk factors from Carhart (1997). *PS* is the traded liquidity factor of Pastor and Stambaugh (2003) and is estimated jointly with the Carhart (1997) factors. *PEAD* beta captures a fund's exposure to short-horizon anomalies as introduced by Daniel, Hirshleifer, and Sun (2019), and *FIN* represents a long-horizon factor that exploits more long-horizon mispricing. We estimate this as a three-factor model similar to Daniel, Hirshleifer, and Sun (2019). The long-horizon factor is based on the information in managers' decisions to issue or repurchase equity in response to persistent mispricing. The short-horizon earnings surprise factor is motivated by investor inattention and evidence of short-horizon underreaction to earnings. *Capital Commitment* is the standardized fraction of total TNA that is invested through shares with either front- or back- load fee. The control variables are defined in Table A1 of the Appendix. The constant term is included but not reported. The t-statistics adjusted for serial correlation using Newey and West (1987) are reported in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Systematic Risk Exposure						
	MKT	SMB	HML	UMD	PS liquidity	PEAD	Fin
Capital Commitment	-0.007**	-0.010**	0.009	0.000	0.003**	-0.006	0.015***
	(-2.36)	(-2.08)	(1.49)	(0.19)	(2.12)	(-1.38)	(2.63)
Size (log(TNA))	-0.003*	-0.006***	-0.010***	0.003**	0.003***	0.008***	-0.010***
	(-1.66)	(-2.68)	(-2.94)	(2.17)	(3.68)	(3.44)	(-3.44)
Family Size	0.004	0.016***	0.005	-0.007***	0.003**	-0.007*	-0.003
	(1.39)	(3.61)	(0.88)	(-3.41)	(2.09)	(-1.67)	(-0.56)
Family Funds (log)	0.007*	-0.023***	-0.012	0.013***	-0.008***	0.008	0.004
	(1.93)	(-3.44)	(-1.52)	(4.33)	(-4.17)	(1.26)	(0.59)
Expense Ratio	0.043***	0.122***	-0.095***	-0.002	-0.008**	0.025**	-0.152***
	(5.15)	(10.20)	(-5.66)	(-0.36)	(-2.12)	(2.08)	(-10.04)
Load Fee	-0.003***	-0.000	0.006**	-0.002**	0.001	-0.003	0.003
	(-2.69)	(-0.25)	(2.32)	(-1.97)	(0.83)	(-1.49)	(1.22)
Fund Cash	-0.006***	0.001**	0.003***	-0.001***	0.000	-0.002***	0.001
	(-11.20)	(2.09)	(4.19)	(-5.17)	(0.27)	(-3.14)	(1.02)
Fund Flows	-0.000***	0.001***	0.001***	0.000**	-0.000	0.000	0.001***
	(-5.35)	(4.03)	(5.50)	(1.97)	(-0.15)	(0.15)	(4.84)
Past Year Returns	-0.056***	0.061***	0.095***	0.107***	0.062***	0.159***	0.108***
	(-5.87)	(4.62)	(4.65)	(9.63)	(8.22)	(8.18)	(4.99)
Time x Style FE	Y	Y	Y	Y	Y	Y	Y
Observations	102329	102329	102329	102329	102329	102329	102329
Adjusted r^2	0.184	0.583	0.175	0.132	0.240	0.222	0.296

Table 8: Portfolio Strategies and Capital Commitment

The table reports the results of regressing proxies for portfolio strategies on the fund's *Capital Commitment*. *Illiquidity* is the weighted average of the Amihud (2002) illiquidity measure across portfolio stocks. *R&D* represents the portfolio's value-weighted average of R&D expense from Compustat, scaled by company assets. *Patents* is the value-weighted number of patents from KPSS patent data (1926-2010) as obtained from Kogan, Papanikolaou, Seru, and Stoffman (2017) over assets. *Fire-sale Stocks* represents the standardized outflow-induced funds selling pressure at the stock level as in Edmans, Goldstein, and Jiang (2012), averaged (using value weights) across the fund portfolio. These variables are measured during the next quarter. *Capital Commitment* is the percentage of fund TNA in share classes with either front or back load fee. We standardize all the dependent variables and the main explanatory variables. The control variables are defined in Table A1 of the Appendix. Residuals are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Iliquidity	R&D	Patents	Fire-sale Stocks
Capital Commitment	0.026**	0.034**	0.029**	0.021*
	(2.01)	(2.01)	(2.26)	(1.94)
Size (log(TNA))	-0.020***	0.001	-0.007	-0.032***
	(-3.24)	(0.12)	(-1.05)	(-4.79)
Family Size	-0.022	-0.036*	-0.047***	0.012
	(-1.22)	(-1.88)	(-2.58)	(1.01)
Family Funds (log)	-0.037*	0.063***	0.025	-0.049***
	(-1.65)	(2.60)	(1.12)	(-2.80)
Load Fee	0.009*	-0.021**	-0.011**	-0.003
	(1.71)	(-2.46)	(-2.17)	(-0.54)
Past Year Returns	-0.401***	0.323***	0.263***	-0.438***
	(-5.81)	(5.42)	(3.94)	(-9.04)
Flow Volatility	0.004*	0.014***	0.015***	0.008***
	(1.93)	(4.02)	(6.51)	(4.36)
Time x Style FE	Y	Y	Y	Y
Observations	109675	109675	90167	109675
Adjusted r^2	0.210	0.125	0.253	0.081

Table 9: Stock Selection and *WSJ* Rankings: IV Approach

This table presents estimates of the effect of the fund's capital commitment on managers' stock selections using instrumental variables methods. In the first stage, the percentage of fund TNA corresponding to shares with entry or exit load fees (*Capital Commitment*) is instrumented with the *WSJ Discontinuity* from Kaniel and Parham (2017): a variable that takes a value of one if the fund belongs to the 10 top funds in the "Category Kings" ranking list of the *Wall Street Journal* (WSJ), and zero otherwise. *WSJ Rank* denotes the actual rank within the top 10. In the second stage, we repeat the regressions in Table 8 after replacing *Capital Commitment* with the instrumented variable from the first stage. *Illiquidity* is the weighted average of the Amihud (2002) illiquidity measure across portfolio stocks. *R&D* represents the portfolio's value-weighted average of R&D expense from Compustat, scaled by company assets. *Patents* is the value-weighted number of patents from KPSS patent data (1926-2010) as obtained from Kogan, Papanikolaou, Seru, and Stoffman (2017) over assets. *Fire-sale Stocks* represents the standardized outflow-induced funds selling pressure at the stock level as in Edmans, Goldstein, and Jiang (2012), averaged (using value weights) across the fund portfolio. These variables are measured during the next quarter. These variables are measured during the next quarter. The control variables are defined in Table A1 of the Appendix. Residuals are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	First Stage	Iliquidity	R&D	Patents	Fire-sale Stocks
Discontinuity	-0.078***				
	(-5.40)				
Rank	0.000***				
	(2.80)				
Locked-up Predicted		0.396**	0.799***	0.485*	0.215
		(2.00)	(4.58)	(1.82)	(1.03)
Size (log(TNA))		-0.044***	0.028***	-0.004	-0.035***
		(-5.63)	(3.62)	(-0.36)	(-4.64)
Family Size		-0.048***	0.003	0.011	-0.043***
		(-3.28)	(0.27)	(0.74)	(-3.52)
Family Funds (log)		0.066***	-0.003	-0.029	0.055***
		(3.45)	(-0.17)	(-1.31)	(2.87)
Load Fee		0.013***	0.003	0.008**	0.005
		(2.68)	(1.05)	(2.00)	(1.38)
Past Year Returns		-0.158***	0.368***	0.402***	-0.165***
		(-4.90)	(8.54)	(7.10)	(-4.73)
Flow Volatility		0.002	0.006***	0.003	0.004***
		(1.06)	(3.92)	(1.50)	(2.67)
Time x Style FE	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y
Observations	87958	58827	58827	51584	58809
Adjusted r^2	0.024	0.643	0.692	0.610	0.414

Table 10: Fund Flows-Performance Sensitivity and Capital Commitment

The table reports the results of regressing the fund's level of *Fund Flows* scaled by the fund's TNA. *Commitment Dummy* is an indicator variable that, for every fund and quarter, takes a value of one (zero) if the fund's fraction of TNA that is invested through share classes with entry or exit loads (including front- and back-end load shares) is in the top (bottom) quartile of the sample. Every quarter, each fund is given a quartile *Rank* based on the fund's gross performance, defined as the fund's gross past 12 months return net of the median value of that of all funds within the same investment objective. In columns 2-5, funds are sorted into quarterly *Low, Mid,* and *High* (performance) rank terciles based on their quarterly gross performance. The control variables are defined in Table A1 of the Appendix. Residuals are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Fund Flows				
	(1)	(2)	(3)	(4)	(5)
Commitment Dummy	0.069***	0.053	0.059***	0.040***	0.041
	(3.49)	(1.52)	(3.49)	(2.92)	(1.16)
Rank	0.323***				
	(14.02)				
Commitment Dummy x Rank	-0.068**				
	(-2.36)				
Low Rank		0.845***			0.050
		(5.96)			(0.31)
Commitment Dummy x Low Rank		-0.140			0.061
		(-0.81)			(0.31)
Mid Rank			0.378***		0.232***
			(13.76)		(7.38)
Commitment Dummy x Mid Rank			-0.080**		-0.031
			(-2.34)		(-0.80)
High Rank				1.691***	1.170***
				(12.83)	(8.23)
Commitment Dummy x High Rank				-0.364**	-0.342*
				(-2.15)	(-1.87)
Size (log(TNA))	-0.043***	-0.042***	-0.043***	-0.041***	-0.042***
	(-13.27)	(-12.92)	(-13.18)	(-12.82)	(-13.20)
Family Size	0.011*	0.013**	0.011**	0.011*	0.010*
	(1.90)	(2.30)	(1.99)	(1.92)	(1.80)
Family Funds (log)	0.009	0.005	0.008	0.011	0.011
	(1.18)	(0.70)	(1.08)	(1.39)	(1.42)
Expense Ratio	-0.045***	-0.038***	-0.044***	-0.054***	-0.051***
	(-3.31)	(-2.76)	(-3.26)	(-3.95)	(-3.76)
Load Fee	-0.001	-0.001	-0.001	-0.000	-0.000
	(-0.20)	(-0.18)	(-0.24)	(-0.04)	(-0.10)
Fund Age (log)	-0.104***	-0.107***	-0.104***	-0.102***	-0.102***
	(-13.51)	(-13.75)	(-13.53)	(-13.17)	(-13.35)
Time x Style FE	Y	Y	Y	Y	Y
Observations	77376	77376	77376	77376	77376
Adjusted r^2	0.228	0.222	0.227	0.227	0.229

Table 11: Household Portfolio Turnover and Share Classes

The table reports the results of regressing the portfolio turnover of individual investors onto the mutual fund share classes choice. The dependent variable is the monthly portfolio turnover for each household. *Front-Load, Back-Load, Level-Load*, and *No-Load* represent the fraction of investors' portfolio assets invested in the corresponding mutual fund share class. We standardize these explanatory variables. The control variables are the investor's marginal tax rate, wealth, and indicator variables for sex, age, marital status, and homeownership. We include investment style (conservative, income, growth, and speculation) times date, and investor knowledge (extensive, good, limited, none) times date fixed effects. Standard errors are clustered at the investor level. Our sample includes monthly observations for 27,536 individual investors who held at least one mutual fund between January 1991 and December 1996. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Portfolio Turnover			
	(1)	(2)	(3)	(4)
Front-Load	-0.553***			
	(-19.07)			
Back-Load		0.056*		
		(1.89)		
Level-Load			0.213***	
			(5.54)	
No-Load				0.371***
				(10.83)
Tax	1.141**	1.181**	1.153**	1.080**
	(2.39)	(2.47)	(2.41)	(2.25)
Wealth (log)	0.027**	0.030**	0.031**	0.032***
	(2.21)	(2.45)	(2.51)	(2.63)
Male	-0.016	-0.023	-0.019	0.003
	(-0.16)	(-0.24)	(-0.20)	(0.03)
Under 45	0.057	0.049	0.042	0.038
	(0.76)	(0.65)	(0.55)	(0.50)
Married	-0.030	-0.051	-0.050	-0.043
	(-0.42)	(-0.70)	(-0.68)	(-0.58)
Homeownership	-0.046	-0.026	-0.030	-0.040
	(-0.26)	(-0.14)	(-0.17)	(-0.23)
Style x Time FE	Y	Y	Y	Y
Knowledge FE x Time FE	Y	Y	Y	Y
Observations	280,994	280,994	280,994	280,994
Adjusted R^2	0.014	0.011	0.011	0.013

Table 12: Investment Horizon Disclosure: Fund Prospectus

This table presents estimates of how explicit funds' prospectus are regarding their investment horizon. The dependent variable is the number of times the word "long-term" appears in the fund prospectus. The main explanatory variable (*No-Load Family*) is a indicator variable for fund families with funds offered in no-load share classes. We also include the natural logarithm of the total number of words in the fund's prospectus (*Total Words*). The remaining control variables are defined in Table A1 of the Appendix. Residuals are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Long-term Words			
	(1)	(2)	(3)	(4)
No-Load Family	6.098**	7.734**	8.311***	8.472***
	(2.29)	(2.58)	(2.82)	(2.82)
Total Words	28.100***	28.189***	28.041***	28.118***
	(7.44)	(7.23)	(7.35)	(7.30)
Size (log(TNA))		1.576	1.710	1.747
		(1.36)	(1.53)	(1.53)
Family Size		-0.553	-0.773	-0.812
		(-0.82)	(-1.08)	(-1.12)
Expense Ratio		6.933	4.429	4.200
		(1.38)	(0.91)	(0.85)
Load Fee		-1.441	-1.177	-1.168
		(-0.84)	(-0.74)	(-0.72)
Fund Age (log)		-5.944*	-4.939	-4.881
		(-1.76)	(-1.56)	(-1.52)
Time FE	Y	Y	Y	N
Style FE	N	N	Y	N
Time FE x Style FE	N	N	N	Y
Observations	17914	17914	17914	17912
Adjusted r^2	0.291	0.295	0.308	0.300

Appendix

Table A1: Variable Definitions

Variable	Definition
Total Net Assets by Share Class	
Capital Commitment	Percentage of the fund's total net asset (TNA) invested in shares with a front-end load $>$ 1 percent (typically, class A) or shares with no front-end load and a contingent deferred sales charge (CDSC) $>$ 2 percent (typically, class B).
Front Investors	Percentage of the fund's TNA invested in shares with a front-end load $>$ 1 percent (typically, class A).
Back Investors	Percentage of the fund's TNA invested in shares with no front-end load and a contingent deferred sales charge (CDSC) $>$ 2 percent (typically, class B).
Level Investors	Percentage of the fund's TNA invested in shares with a front-end load $\leq$ 1 percent, CDSC $\leq$ 2 percent, and 12b-1 fee $\geq$ 0.25 percent.
No-load Investors	Percentage of the fund's TNA invested in shares with front-end load = 0 percent, CDSC = 0 percent, and 12b-1 fee $<$ 0.25 percent.
Fund and Family Characteristics	
Fund Age	Number of years since fund inception date (years).
Fund Size	Fund's Total Net Assets (TNA) under management (USD Million).
Fund Performance	Alpha from regressing buy-and-hold portfolio returns on the corresponding buy-and-hold Carhart (1997) four factors with the same holding horizon.
Family Size	TNA of all funds in the family, excluding the fund itself.
Family Funds	Number of funds in the fund family.
Load Fee	Average front or rear load fee (in %).
Redemption Fee	Dummy variable that takes a value of one if the fund charges redemption fees.
Expense Ratio	Total annual expenses and fees divided by year-end TNA (in %).
Turnover	Minimum of aggregate purchases and sales of securities divided by average TNA over the calendar year (in %).
Institutional Investors	Percentage of the fund's TNA invested in institutional shares class
Fire-Sale Stocks	Weighted average holding of the outflow-induced stock level pressure variable as in Edmans, Goldstein, and Jiang (2012), averaged across the fund portfolio. The stock-level measure captures the hypothetical (signed) net selling by all mutual funds that have experienced outflows (of at least 5% of total assets). The dollar outflow is scaled by the stock's dollar trading volume.
Flow Volatility	Standard deviation of monthly inflows and outflows in the following 24 months.
Flow Prediction	R-squared from regressing fund flows on past cash holdings using 36 months of observations.
Fund Flows	Net growth in fund assets beyond reinvested dividends (Sirri and Tufano, 1998) over the past one year (in %).
Trading Duration	Weighted-average (weighted by the size of each stock position) of number of years the fund has held equities in the portfolio over the last five years.
Manager Tenure	Number of years since fund manager started working for the fund family.
Evaluation Period	Average evaluation period for manager performance bonus.
Gross Returns	Monthly portfolio gross return (in %). The gross monthly returns are computed by adding 1/12 of the expense ratio.
Net Returns	Monthly portfolio net return (in %).
Gross Performance	Portfolio gross return minus the median value of the return of all the funds within the same investment objective (in %).
Illiquidity	Weighted average of the Amihud (2002) illiquidity measure across portfolio stocks.
R&D	Portfolio's value-weighted average of R&D expense from Compustat scaled by company assets (in %).
Pattens	is the value-weighted number of patents from KPSS patent data (1926-2010) as obtained from Kogan, Papanikolaou, Seru, and Stoffman (2017) over assets.

Table A2: Fund Flow Stability and Capital Commitment: Inflows vs. Outflows

The table reports the results of regressing fund flow volatility on investor capital commitment and fund characteristics. The dependent variable, *Flow Volatility*, is the standard deviation of monthly inflows, outflows, and net flows in the following 24 months, respectively. *Capital Commitment* is the percentage of fund total net assets in share classes with either front- or back-load fee. We standardize the dependent and main explanatory variables. The control variables are defined in Table A1 of the Appendix. Standard errors are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

		Fund Flow Volatility	
	Inflows	Outflows	Net Flows
Capital Commitment	-0.105***	-0.120***	-0.124***
	(-6.19)	(-7.58)	(-7.58)
Size (log(TNA))	-0.145***	-0.124***	-0.188***
	(-14.90)	(-14.16)	(-20.47)
Family Size	-0.020	-0.007	0.002
	(-1.36)	(-0.54)	(0.13)
Family Funds (log)	0.063***	0.010	0.024
	(2.99)	(0.52)	(1.10)
Expense Ratio	0.064*	-0.006	0.004
	(1.94)	(-0.21)	(0.11)
Load Fee	0.005	-0.008	-0.010
	(0.74)	(-1.31)	(-1.60)
Fund Age (log)	0.058***	0.090***	0.057***
	(3.08)	(5.52)	(2.98)
Noload Fund	0.117**	0.180***	0.146**
	(2.08)	(2.71)	(2.38)
Time x Style FE	Y	Y	Y
Observations	77041	77041	77041
Adjusted r^2	0.152	0.132	0.253

Table A3: Trading Duration and Capital Commitment: Family Fixed Effects

The table reports the results of regressing the manager's *Trading Duration* on the percentage of fund total net assets in share classes with either front or back load fee and fund characteristics. *Trading Duration*, introduced in Cremers and Pareek (2016), is based on quarter-end holdings and measures the weighted-average (weighted by the size of each stock position) length of time that the fund has held equities in the portfolio over the last five years. We standardize the dependent variable and the main explanatory variables. The control variables are defined in Table A1 of the Appendix. Standard errors are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Trading Duration			
	(1)	(2)	(3)	(4)
Capital Commitment	0.045***		0.039**	0.042**
	(2.74)		(2.11)	(2.48)
Back Investors		0.043***		
		(3.48)		
Front Investors		0.034**		
		(2.25)		
No Load Investors			-0.013	
			(-0.71)	
Institutional Investors				-0.012
				(-0.79)
Size (log(TNA))	0.111***	0.110***	0.111***	0.111***
	(14.72)	(14.71)	(14.72)	(14.67)
Family Size	-0.004	-0.007	-0.004	-0.003
	(-0.25)	(-0.51)	(-0.28)	(-0.22)
Family Funds (log)	-0.094***	-0.096***	-0.093***	-0.093***
	(-3.42)	(-3.52)	(-3.40)	(-3.39)
Expense Ratio	-0.153***	-0.181***	-0.157***	-0.157***
	(-4.55)	(-5.02)	(-4.62)	(-4.61)
Load Fee	-0.015**	-0.015**	-0.015**	-0.015**
	(-2.27)	(-2.22)	(-2.28)	(-2.25)
Fund Cash	-0.003**	-0.003**	-0.003**	-0.003**
	(-2.21)	(-2.15)	(-2.22)	(-2.20)
Fund Flows	-0.003***	-0.003***	-0.003***	-0.003***
	(-11.03)	(-11.09)	(-11.02)	(-11.03)
Time x Style FE	Y	Y	Y	Y
Family FE	Y	Y	Y	Y
Observations	122474	122474	122474	122474
Adjusted r^2	0.412	0.413	0.412	0.412

Table A4: Trading Duration and Capital Commitment: Alternative Duration Measures

The table reports the results of regressing alternative measures of manager holding horizon on investors' *Capital Commitment*. *Turnover* ratio is the minimum of aggregate sales or purchases of stocks divided by the fund's total net assets (as reported annually in CRSP). The other three measures come from Lan, Moneta, and Wermers (2015). The first measure is the "simple" horizon measure (SHM), which calculates the holding horizon of stocks in a given fund portfolio as the length of time from the initiation of a position to the time that the stock is fully liquidated by the fund. The second measure is the "Ex-Ante" measure, which uses only current and past information. The third measure (FIFO) allows for the possibility that position changes may also be informative about the intended holding horizon and tracks inventory layers of each stock held by each fund. It assumes that the stocks purchased first by a fund are sold first. *Capital Commitment* is the percentage of fund TNA in share classes with either front or back load fee. We standardize the dependent variable and the main explanatory variables. The control variables are defined in Table A1 of the Appendix. Standard errors are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Alternative Duration Meassures			
	Turnover	Duration SHM	Duration Ex-ante	Duration FIFO
Capital Commitment	-0.080***	0.040**	0.055***	0.056***
	(-4.98)	(2.10)	(3.21)	(2.82)
Size (log(TNA))	-0.060***	0.110***	0.129***	0.119***
	(-8.87)	(11.29)	(13.94)	(11.88)
Family Size	-0.047***	0.036**	0.032**	0.043***
	(-3.06)	(2.38)	(2.26)	(2.82)
Family Funds (log)	0.133***	-0.172***	-0.167***	-0.191***
	(6.04)	(-6.93)	(-6.87)	(-7.47)
Expense Ratio	0.269***	-0.205***	-0.131***	-0.211***
	(7.35)	(-4.73)	(-3.49)	(-4.72)
Load Fee	-0.005	0.011	-0.004	0.001
	(-0.78)	(1.33)	(-0.55)	(0.15)
Fund Cash	0.002	0.004**	0.003*	0.006***
	(1.22)	(2.33)	(1.82)	(2.98)
Fund Flows	0.002**	-0.000	-0.004***	-0.000
	(2.44)	(-1.24)	(-12.02)	(-1.15)
Noload Fund	-0.016	-0.002	-0.045	-0.022
	(-0.35)	(-0.04)	(-0.91)	(-0.39)
Time x Style FE	Y	Y	Y	Y
Observations	129500	129500	129500	129500
Adjusted r^2	0.097	0.149	0.226	0.152

Table A5: Trading Duration and Capital Commitment: Additional Controls

The table reports the results of regressing the manager's *Trading Duration* on the percentage of fund TNA in share classes with either front or back load fee and fund characteristics. *Trading Duration*, introduced in Cremers and Pareek (2016), is based on quarter-end holdings and measures the weighted-average (weighted by the size of each stock position) length of time that the fund has held equities in the portfolio over the last five years. *Capital Commitment* is the percentage of fund TNA in share classes with either front or back load fee. *Institutional Investors* represent the percentage of fund TNA in the corresponding share classes. *Noload Fund* is an indicator variable for funds without load share classes. *Redemption Fee* is a dummy variable for funds that charge a fee when investors redeem their shares. *Manager Evaluation Period* is number of years over which manager performance is evaluated. The control variables are defined in Table A1 of the Appendix. Standard errors are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Trading Duration					
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Commitment	0.052***	0.042**	0.042**	0.128***	0.136***	0.138***
	(3.13)	(2.38)	(2.37)	(3.88)	(3.92)	(3.94)
Redemption Fee	0.039	0.034	0.035			
	(1.02)	(0.91)	(0.92)			
Manager Evaluation Period				0.115**	0.119**	0.117**
				(2.27)	(2.34)	(2.28)
Institutional Investors		-0.042**	-0.042**		0.028	0.030
		(-2.49)	(-2.46)		(0.87)	(0.91)
Noload Fund			0.006			0.054
			(0.13)			(0.52)
Size (log(TNA))	0.115***	0.114***	0.114***	0.126***	0.128***	0.130***
	(13.21)	(13.13)	(13.01)	(8.40)	(8.48)	(8.48)
Family Size	0.019	0.015	0.015	0.071***	0.072***	0.071***
	(1.42)	(1.13)	(1.11)	(2.70)	(2.73)	(2.63)
Family Funds (log)	-0.122***	-0.115***	-0.115***	-0.188***	-0.190***	-0.187***
	(-5.49)	(-5.14)	(-5.09)	(-4.71)	(-4.72)	(-4.56)
Expense Ratio	-0.241***	-0.260***	-0.259***	-0.383***	-0.362***	-0.356***
	(-6.51)	(-7.01)	(-6.89)	(-4.41)	(-4.13)	(-4.00)
Load Fee	-0.004	-0.003	-0.003	0.005	0.004	0.005
	(-0.58)	(-0.35)	(-0.32)	(0.32)	(0.26)	(0.34)
Fund Cash	0.000	-0.000	-0.000	0.011**	0.011**	0.011**
	(0.01)	(-0.06)	(-0.05)	(2.06)	(2.07)	(2.09)
Fund Flows	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(-9.06)	(-9.22)	(-9.22)	(-5.15)	(-5.12)	(-5.13)
Time x Style FE	Y	Y	Y	Y	Y	Y
Observations	122481	122481	122481	30719	30719	30719
Adjusted r^2	0.254	0.255	0.255	0.316	0.316	0.316

Table A6: Fund Performance and Trading Duration

The table reports the results of regressing fund performance on the Cremers and Pareek (2016) measure of *Trading Duration* and some fund characteristics. Trading duration is based on quarter-end holdings and measures the weighted-average (weighted by the size of each stock position) length of time that the fund has held equities in the portfolio over the last five years. Fund performance corresponds to the alpha obtained from the Carhart (1997) four factors model. We use both gross (before fee) and net (after fee) returns. *Capital Commitment* is the percentage of fund TNA in share classes with either front or back load fee. *Institutional Investors* represent the percentage of fund TNA in the corresponding share classes. *Noload Fund* is an indicator variable for funds without load share classes. We standardize the dependent variable and the main explanatory variables. The control variables are defined in Table A1 of the Appendix. Standard errors are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Fund Performance (Gross Returns)			Fund Performance (Net Returns)		
	(1)	(2)	(3)	(4)	(5)	(6)
Trading Duration	0.059***	0.060***	0.060***	0.060***	0.061***	0.060***
	(8.00)	(8.13)	(8.03)	(8.12)	(8.22)	(8.12)
Institutional Investors		0.012*	0.012*		0.010	0.011
		(1.67)	(1.76)		(1.47)	(1.55)
Noload Fund			0.038*			0.036
			(1.70)			(1.55)
Size (log(TNA))	-0.035***	-0.034***	-0.034***	-0.035***	-0.034***	-0.034***
	(-7.04)	(-6.83)	(-6.76)	(-7.17)	(-6.97)	(-6.90)
Family Size	0.013***	0.013***	0.013***	0.015***	0.015***	0.015***
	(3.53)	(3.56)	(3.47)	(3.91)	(3.94)	(3.84)
Expense Ratio	-0.068***	-0.059**	-0.055**	-0.149***	-0.141***	-0.137***
	(-2.99)	(-2.46)	(-2.23)	(-6.26)	(-5.59)	(-5.28)
Front Load	-0.186	-0.257	-0.082	-0.159	-0.221	-0.056
	(-0.63)	(-0.85)	(-0.25)	(-0.53)	(-0.73)	(-0.17)
Back Load	0.082	0.084	0.219	0.147	0.148	0.276
	(0.22)	(0.23)	(0.58)	(0.40)	(0.40)	(0.74)
Fund Cash	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*
	(1.70)	(1.76)	(1.78)	(1.79)	(1.83)	(1.86)
Fund Flows	0.057***	0.057***	0.057***	0.057***	0.057***	0.057***
	(25.55)	(25.56)	(25.57)	(25.54)	(25.55)	(25.56)
Time x Style FE	Y	Y	Y	Y	Y	Y
Observations	135161	135161	135161	135161	135161	135161
Adjusted r^2	0.215	0.215	0.215	0.216	0.216	0.216

Table A7: Differences in Means from the WSJ "Category Kings" Discontinuity

This table shows the differences in means in the quarter after funds are ranked 10 relative to 11 following the Wall Street Journal "Category Kings" ranking list from Kaniel and Parham (2017). All variables are defined in Table A1 of the Appendix. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	T-Test Analysis: Ranked 10 vs Ranked 11		
	Ranked 10	Ranked 11	Difference
Next Quarter Flows	12.083	7.563	4.520*
Next Quarter Load-Level Flows	23.940	12.456	11.484**
Next Quarter Locked-up Flows	15.844	10.909	4.936
Next Quarter No-Load Flows	16.047	13.464	2.582
Next Year Turnover	0.939	0.905	0.034
Next Year Duration	4.718	5.276	-0.557*
Next Year Active Share	0.865	0.841	0.024**
Next Year Evaluation Period	4.513	4.755	-0.243
Next Quarter Locked_up Assets	-0.151	-0.032	-0.118*
Next Quarter NoLoad Assets	0.002	-0.067	0.068
Next Quarter Level Assets	0.161	0.045	0.115
Observations	1093		

Table A8: Stock Selection and *WSJ* Rankings: Only No-Load Funds

The table reports the results of regressing proxies for portfolio strategies on the variable *WSJ Discontinuity* from Kaniel and Parham (2017): a variable that takes a value of one if the fund belongs to the 10 top performance funds in the "Category Kings" ranking list of the *Wall Street Journal* and zero otherwise. *Illiquidity* is the weighted average of the Amihud (2002) illiquidity measure across portfolio stocks. *R&D* represents the portfolio's value-weighted average of R&D expense from Compustat, scaled by company assets. *Patents* is the value-weighted number of patents from KPSS patent data (1926-2010) as obtained from Kogan, Papanikolaou, Seru, and Stoffman (2017) over assets. *Fire-sale Stocks* represents the standardized outflow-induced funds selling pressure at the stock level as in Edmans, Goldstein, and Jiang (2012), averaged (using value weights) across the fund portfolio. These variables are measured during the next quarter. The subsample includes only *Pure No-Load* funds (funds with only no-load class shares). The control variables are defined in Table A1 of the Appendix. Residuals are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Iliquidity	R&D	Patents	Fire-sale Stocks
Discontinuity	-0.025	-0.014	-0.038	0.025
	(-0.90)	(-0.62)	(-0.86)	(0.66)
Rank	0.000***	-0.000	-0.000	0.001***
	(3.49)	(-0.78)	(-1.02)	(3.75)
Size (log(TNA))	-0.037***	0.052***	0.004	-0.023
	(-3.22)	(3.10)	(0.17)	(-1.20)
Family Size	-0.058***	0.044**	-0.002	-0.022
	(-2.75)	(2.27)	(-0.07)	(-0.67)
Family Funds (log)	0.062**	-0.066*	0.002	0.018
	(2.20)	(-1.77)	(0.05)	(0.65)
Flow Volatility	-0.002	0.005**	0.004	0.002
	(-1.10)	(2.33)	(1.47)	(0.73)
Time x Style FE	Y	Y	Y	Y
Observations	17236	17236	14777	17233
Adjusted r^2	0.699	0.742	0.633	0.487

Table A9: Household Mutual Fund Holdings Turnover and Share Classes

The table reports the results of regressing the turnover of mutual fund shares on several fund characteristics. The dependent variable is the monthly turnover of mutual fund shares held by each household. *Front-Load, Back-Load and Level-Load*, and *No-Load* are indicator variables for the corresponding mutual fund share classes. The control variables are mutual fund size, fee, age and indicator variables for index and US equity fund. We include investor times month fixed effects. Standard errors are clustered at the investor level. Our sample includes monthly observations for 1,001 US mutual funds and 27,536 individual investors with holdings in at least one mutual fund from January 1991 to December 1996. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Security Turnover			
	(1)	(2)	(3)	(4)
Front-Load	-0.072***			
	(-10.44)			
Back-Load		0.014		
		(0.56)		
Level-Load			0.183***	
			(7.78)	
No-Load				0.066***
				(12.53)
Fund Size	-0.021***	-0.022***	-0.024***	-0.023***
	(-5.43)	(-5.90)	(-6.37)	(-5.98)
Fund Fee	-0.087***	-0.095***	-0.119***	-0.085***
	(-8.60)	(-9.43)	(-10.22)	(-8.36)
Fund Age	-0.003***	-0.003***	-0.004***	-0.003***
	(-12.35)	(-12.78)	(-13.03)	(-12.94)
Index Fund	-0.064**	-0.064**	-0.072**	-0.060**
	(-2.22)	(-2.20)	(-2.44)	(-2.04)
Equity Fund	-0.093***	-0.094***	-0.097***	-0.086***
	(-12.36)	(-12.53)	(-12.71)	(-11.35)
Investor x Time FE	Y	Y	Y	Y
Observations	2,652,525	2,652,525	2,652,525	2,652,525
Adjusted R^2	0.853	0.853	0.853	0.853

Table A10: Redemption Fee and Capital Commitment

This table presents estimates of the probability that a fund charges a redemption fee on the fund's capital commitment, using a linear probability model. *Capital Commitment* is the (standardized) percentage of fund total net assets in share classes with either front or back load fee. The control variables are defined in Table A1 of the Appendix. Residuals are clustered at the fund level. * denotes significance at the 10% level, ** denotes significance at the 5% level and *** denotes significance at the 1% level.

	Redemption Fee			
	(1)	(2)	(3)	(4)
Capital Commitment	-0.044***	-0.059***	-0.051***	-0.052***
	(-5.95)	(-6.97)	(-6.19)	(-6.24)
Size (log(TNA))		0.001	0.002	0.003
		(0.23)	(0.62)	(0.65)
Family Size		-0.021***	-0.023***	-0.023***
		(-5.34)	(-6.02)	(-5.98)
Expense Ratio		0.115***	0.084***	0.085***
		(6.91)	(5.04)	(5.05)
Load Fee		0.006*	0.007**	0.007**
		(1.68)	(2.03)	(2.04)
Fund Age (log)		0.007	0.007	0.008
		(0.73)	(0.71)	(0.81)
Time FE	Y	Y	Y	N
Style FE	N	N	Y	N
Time FE x Style FE	N	N	N	Y
Observations	135692	135692	135692	135671
Adjusted r^2	0.017	0.062	0.079	0.076