Contract Evaluation Horizon and Fund Performance *

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Abstract

Mutual funds face the risk of withdrawals if they perform poorly in the short term, which encourages manager myopia. We show that fund families can insulate managers from this funding pressure via compensation tied to long-term fund performance. Managers with long-horizon contracts are more likely to undertake long-term investments and outperform their constrained peers. Since long-horizon pay does not shut off the funding pressure but simply insulates the manager from it, not all families can offer these contracts. Long-horizon contracts are more prevalent in families that cater to patient investors and have more resources to buffer liquidity shocks.

JEL Classification: G10, G23

Keywords: mutual funds, evaluation horizon, compensation contracts, performance, managerial myopia

1 Introduction

Investors often evaluate their managers based on recent fund performance. The resulting funding pressure from investor flows can significantly curtail the success of long-horizon arbitrage strategies and, consequently, discourage portfolio managers from investing in opportunities that take longer to converge (Shleifer and Vishny (1997)). Therefore, the threat of investor redemptions acts as an important constraint on fund managers, effectively limiting their opportunity set to investments with short-term payoffs. Additionally, this short-horizon focus also has important asset pricing implications (Hodor and Zapatero (2023)).

One way to insulate a fund from short-term funding pressure is to use *ex ante* capital structure adjustments that curb investor flows, such as lockups or withdrawal restrictions. However, these levers are not commonly available to mutual funds. Instead, mutual funds are largely limited to employing loads as the main tool to discourage investors from short-horizon investing (Barber, Odean, and Zheng (2003)).[1] Loads are likely ineffective in disciplining individual investors who do not quite understand the punitive nature of these fees. Additionally, they are often waived for institutional investors who are more price conscious. Accordingly, Giannetti and Kahraman (2018) show that open-end mutual fund managers are more myopic than their peers managing hedge funds and closed-end mutual funds.

In this paper we examine the role of compensation contracts as an alternative way to insulate mutual fund managers from the short-term pressure of their investors. Specifically, we focus on the length of the evaluation horizon used to determine the performance-based incentive component of managerial pay. Since long-horizon contracts decouple manager compensation from short-term fund performance, such contacts can restore managers' incentives to trade on long-term mispricing. Accordingly, we expect that the portfolio holdings and

[1]More recently, some funds have adopted swing pricing, though the practice is not wide-spread in the U.S. The Securities and Exchange Commission proposed a mandatory swing pricing rule but ultimately did not adopt it in 2024.

trades of these managers will reflect a heightened willingness to pursue long-term investment strategies.

Since managers who are evaluated based on long-horizon performance are less constrained, we also hypothesize that they outperform their peers whose pay is tied to short-run performance. These peer managers who face the cost of withdrawals if they perform poorly in the short run (Edelen (1999)) are not only limited to opportunities with short-term payoffs, but investments in these short-term opportunities are also less scalable (van Binsbergen, Han, Ruan, and Xing (2024)). Of course, it is possible that funds offering contracts that impose fewer constraints attract better managers in the first place. Therefore, we perform a series of robustness checks to address endogeneity concerns. Generally, these arguments are consistent with a large literature in corporate finance that shows that firms incentivize CEOs with compensation tied to long-run firm performance, and that long evaluation horizons enhance firm performance (see Stein (1989), Edmans, Gabaix, Sadzik, and Sannikov (2012), and Edmans, Gabaix, and Jenter (2017) for a literature review).

If long horizon contracts increase the set of profitable investment opportunities available to managers, why don't all funds employ long horizon contracts? Unlike trading or redemption restrictions imposed on fund investors, the 'horizon lever' does not directly shut off the funding pressure—it merely insulates the manager from it. Since these contracts do not directly eliminate the cost of investor short-termism on the fund family, we argue that not all fund families can offer these contracts. Funds with long-term investors or those with lower flow-performance sensitivities should be more likely to adopt long-horizon based bonuses. Additionally, long-horizon contracts should also be more prevalent in families that are larger, more reputable, and have a more diversified asset base. Such families are likely to have more resources and flexibility to provide a buffer against temporary liquidity shocks to their member funds.[2]

[2]For example, funds have access to lending channels, such as interfund lending.

To test these hypotheses, we follow Ma, Tang, and Gomez (2019) and Lee, Trzcinka, and Venkatesan (2019) and hand collect data on managerial compensation arrangements for open-end, actively managed U.S. domestic equity funds from the Statement of Additional Information (SAI) for the 2005-2018 sample period. When performance-based incentive compensation is used, funds disclose the horizon on which evaluations are based. We find that evaluation horizons vary significantly among equity funds in our sample, although funds that consider only short-horizon fund performance are quite common. Specifically, when we divide our sample into funds with short-horizon (one year or less) and long horizon (over one year) contracts, short-horizon funds represent a little over half of our sample.[3]

We then integrate our compensation data with the CRSP Survivorship Bias-Free Mutual Fund Database and Morningstar Direct and employ the merged data to test the aforementioned hypotheses. The results strongly support our predictions. First, we show that long-horizon managers hold securities longer, are more likely to engage in arbitrage strategies that take longer to converge, and their fund performance loads more heavily on long-run risk. Interestingly, these funds continue to pursue short-term opportunities as well. This is consistent with an option-like feature: long-horizon contracts alleviate investment constraints and thus increase investment opportunities available to managers, who are now incentivized to more flexibly exploit mispricings regardless of the expected speed of convergence. We then show that funds whose managers are offered long-horizon evaluation contracts outperform peer funds whose managers face short-horizon performance evaluations. This finding is robust to alternative performance measures as well as performance measured at alternative horizons.

We offer several tests to address potential endogeneity concerns. For example, to mitigate the concern that funds with long-horizon contracts are different from those with short-horizon contracts, we provide a matched sample analyis. To mitigate concerns about unobservable managerial characteristics driving our findings, we add (lead) manager fixed effects and also

[3]Unlike Ma, Tang, and Gomez (2019), we only include actively managed domestic equity funds.

show that our results are robust to using across-family fund mergers, which offer a plausibly exogenous shock to managerial contracts. Additionally, we show that manager turnover at long-horizon funds is significantly related to long-horizon performance (but not related to short-term performance), validating that the performance criteria embedded in the contract are used in managerial evaluations.

Consistent with the argument that CEO compensation should be based on long-run performance to prevent managerial short-termism (Edmans, Gabaix, and Jenter (2017)), our results suggest that long-term contracts curtail myopia and are associated with better performance in the mutual fund industry as well. However, they are not optimal for every fund family. We show that these contracts are indeed more prevalent with older and larger funds and families that are therefore more reputable. Funds with long-term investors, such as those in DC pension plans, are also more likely to adopt long-term contracts, as are funds with lower flow-performance sensitivities, that is, funds that cater to more patient clients. Additionally, consistent with the idea that access to temporary liquidity pools matters, we show that long-horizon contracts are significantly related to the availability of interfund lending in the family.

Understanding the characteristics of fund manager compensation contracts and their effects on manager incentives are key economic issues. Our paper is the first study that provides a comprehensive description of the evaluation horizon embedded in mutual fund compensation contracts and examines how evaluation horizon affects fund investment decisions and fund performance. We show that funds that compensate their managers based on long-horizon fund performance outperform funds with a short-evaluation horizon. While our results are consistent with a voluminous literature that studies executive compensation in the corporate setting, they are new to the asset management literature.[4]

[4]Additionally, theoretical research on evaluation horizon in the optimal portfolio manager compensation literature is very limited. Among the few examples are Li and Tiwari (2009) and Cuoco and Kaniel (2011).

The principal-agent conflict in the mutual fund setting is somewhat different from that in nonfinancial firms since funds' investment decisions exhibit two layers of agency: investors delegate to an investment advisor, who then hires a portfolio manager. Nonetheless, there are good reasons to expect that mutual fund managers may exhibit myopia in their investments and that their short-term focus has a negative performance effect. Giannetti and Kahraman (2018) provide empirical evidence that when investors vote with their feet based on recent performance, their short-sighted funding pressure discourages managers from investing in long-horizon mispricings (Stein (2005) and Shleifer and Vishny (1997)).

Our results also contribute to the nascent literature on fund manager compensation in the mutual fund industry. Ma, Tang, and Gomez (2019) provide the first comprehensive description of the various types of compensation contracts for U.S. mutual fund managers, focusing on the 2006 to 2011 period based on data collected from SAI filings. They show that managerial compensation varies across funds and may include fixed salary as well as variable compensation. Additionally, they offer a short description of the evaluation horizon embedded in managerial bonuses but do not study the role of manager evaluation horizon in curbing managerial myopia or enhancing fund performance.

Using the same SAI data, Lee, Trzcinka, and Venkatesan (2019) document that fund managers whose compensation contracts are tied to fund performance raise their portfolio risk when their mid-year performance is close to their announced benchmark, indicating that fund managers' compensation affects their risk taking. In this study we show that, in addition to manager risk shifting, managerial compensation also affects managers' investment horizons and fund performance.

While the SAI data describe the various components of managerial pay, they do not contain information on dollar magnitudes. In contrast, several studies have emerged that use administrative data. Specifically, Ibert, Kaniel, Nieuwerburgh, and Vestman (2018) provide evidence from Sweden, while Bai, Ma, and Mullally (2024) and Du, Cen, Kogan, and Wu (2025) study U.S. tax records of mutual fund managers. While the administrative data only provide aggregate pay figures for each manager across all funds they manage, these aggregate salaries reveal crucial characteristics of the magnitude of managerial pay. For example, the studies show that manager compensation is quite small compared to the total fees collected by funds, upending the long-held practice in the literature of modeling managerial compensation as expense ratio times assets.

Our results are also related to previous papers that examine the relation between investment horizon and fund performance.[5] Investment horizon in these studies is generally inferred from fund holdings and trades. For example, van Binsbergen, Han, Ruan, and Xing (2024) sort funds based on their turnover and show that high-turnover funds generate their value-added from short-horizon trades while low-turnover funds' value-added comes from long-term investments, consistent with an argument that funds specialize in horizon-specific skills.

Similarly, Lan, Moneta, and Wermers (2024) argue that due to costly investor funding pressure arising from short-horizon flow-performance sensitivity, only managers with truly superior insights about long-run returns will undertake long-term investments. That is, the very best managers will self-select into long-horizon funds. The paper then uses fund holdings to infer fund investment horizon. Consistent with the argument, the study finds that long-horizon funds deliver significantly positive alphas. Furthermore, Cremers and Pareek (2016) use portfolio duration determined from the holdings and show that among the funds with highly skilled managers as revealed in high active shares, only those with patient investment strategies outperform.

[5]See, e.g., Cremers and Pareek (2016), van Binsbergen et al. (2024), Lan et al. (2024), and van Binsbergen et al. (2025)

These results are consonant with equilibrium outcomes under the short-sighted funding constraints we discuss in this paper. Specifically, the constraints can force many funds to specialize in short-term investments. Some funds may still pursue long-term opportunities, but only if these are good enough to offset the costs of investor flows. Our paper shows that some funds are able to insulate the manager from the funding constraint. Therefore, our horizon sorts are different from those based on the length of funds' investments: long-horizon funds in our context identify funds whose managers are incentivized to consider long-term investment opportunities through their compensation contracts. That is, our paper simply sorts managers based on whether they are exposed to short-sighted funding constraints. Although we show that managers with long-horizon contracts are, on average, more likely to engage in long-term arbitrage, what differentiates our sort from previous studies is that whether a long-horizon manager ends up exploiting short- or long-term mispricings will ultimately depend on the opportunities available to them.

Finally, our results contribute to the asset management literature on mechanism to alleviate managerial myopia. Hombert and Thesmar (2014) argue that some open-end funds, in particular some hedge funds, are able to reduce their exposure to short-term funding risk by imposing restrictions that constrain investor withdrawals. They show that such restrictions help enhance hedge fund performance, and the performance enhancement concentrates in periods with weak fund performance, which are the periods in which the threat of redemptions is large. Similarly, Gomez et al. (2024) model loads as a committing device and show that funds that charge loads invest for longer horizons and perform better than their peers. In this study we propose an alternative mechanism to insulate fund managers from short-sighted funding pressures, namely, long-horizon contracts.

Our findings have meaningful policy implications. In 2005, the U.S. Securities and Exchange Commission (SEC) adopted the initial disclosure rule on the general structure of portfolio manager compensation. While publicly-listed firms are required to disclose how they pay their executives in great detail and on a regular basis, mutual funds, which collectively manage nearly $30 trillion in assets[6] on behalf of investors, are not required to do so. Frequent, detailed disclosure of fund manager compensation would allow researchers to further study the effects of manager compensation on fund investment and fund performance, and also inform investors on manager pay.

2 Data and Summary Statistics

To test our hypotheses, we follow Ma, Tang, and Gomez (2019) and Lee, Trzcinka, and Venkatesan (2019) by manually collecting data on managerial compensation structures for open-end, actively managed U.S. domestic equity funds from the Statement of Additional Information (SAI) over the 2005–2018 period. Our sample begins in 2005, when the SEC implemented a rule requiring mutual funds to disclose details of their managerial compensation structure in the SAI.[7] While the SAI does not report exact compensation amounts, it provides qualitative information on contract structures.

Typically, manager compensation includes a fixed salary and, in most cases, also a variable component tied to fund performance or assets under management (AUM). For each fund, we create an indicator for whether it pays managers with a variable component and another indicator for whether the variable component is tied to fund performance. If there is a performance-based bonus, the SEC also requires funds to disclose the time horizon used to evaluate manager performance for compensation purposes, which we use to identify each fund manager's performance evaluation horizon.[8] Funds usually disclose that they evaluate the performance of their managers over multiple horizons. For example, Wellington Management discloses that it pays its managers based on their 1- and 3-year performance: "Each Investment

[6]https://www.icifactbook.org/pdf/2025-factbook-quick-facts-guide.pdf

[7]For details of the disclosure requirements, see https://www.sec.gov/rules/final/33-8458.htm.

[8]If fund management is outsourced, we retrieve from the SAI the number of subadvisors and the compensation structure of subadvisor(s).

Professional's incentive payment relating to the relevant Fund is linked to the gross pre-tax performance of the portion of the Fund managed by the Investment Professional compared to the benchmark index and/or peer group identified below over one and three year periods, with an emphasis on three year results." To provide further context, we include three excerpts from SAI documents in EXHIBIT 1 in the Appendix: Wellington Management for 2012, Pioneer for 2012, and T.Rowe Price for 2017.

For each year in our sample period, we classify each fund into one of four manager performance evaluation horizons (1, 3, 5, or 10 years) based on the longest horizon disclosed in their annual document. For example, we classify Wellington Management as having a 3-year evaluation horizon in 2012 according to the disclosure quoted above. Nearly all disclosed evaluation horizons fall into the four categories 1, 3, 5, or 10 years. There are, however, some exceptions during the first two years (2005 and 2006) when the SEC started to require funds to disclose managers' compensation structure. This was due to the lack of standard disclosure guidelines, which were only gradually adopted after the implementation of the SEC rule. For 2005 and 2006, we round the reported evaluation horizon of 4 years to 5 years. There are 59 such cases in total.[9]

We merge the compensation data with fund-level data from the Center for Research in Security Prices (CRSP) Mutual Fund database using fund tickers, or fund names when tickers are not reported in the SEC filings. Tickers became reliably available in fund SEC filings from 2006. The CRSP Mutual Fund database includes fund characteristics, net asset values, and fund returns for each share class at a monthly frequency. We identify index funds using the CRSP index fund indicators and fund names, and exclude them from our sample to focus on actively managed funds.

We aggregate multiple share classes of the same fund into a single fund entity using the MFLINKS fund identifier. When the MFLINKS identifier is unavailable, we use the

[9]Two funds reported evaluation horizons of 7 and 8 years, which we round to 10 years.

CRSP portfolio number as an alternative. The aggregation is done by calculating each fund's total net asset value (NAV) by summing the NAVs across its share classes and computing fund returns as NAV-weighted averages of the share class returns. Fund stock holdings are obtained from the Thomson Reuters Mutual Fund Holdings database and, for the post-2008 period, from the portfolio holdings files of the CRSP Mutual Fund database. Schwarz and Potter (2016) show that the CRSP holdings closely match the regulatory holdings reports after 2008.

Lastly, we obtain information on funds' defined contribution (DC) pension assets from Pensions & Investments (P&I). P&I conducts surveys that poll fund managers about their positions in DC assets. These data have previously been used in Christoffersen and Simutin (2014) and Sialm and Starks (2012). We also obtain fund manager information from the Morningstar Direct database and merge it with the CRSP Mutual Fund database using fund CUSIP numbers, tickers, or, when necessary, a name-matching algorithm. Our final sample consists of 2,952 unique U.S. domestic equity mutual funds spanning the period 2005 to 2018.

Figure 1 plots the number of funds in our sample by manager evaluation horizon ~~and~~ for each year of our sample. The corresponding numbers are reported in Table 1. The one-year evaluation horizon is the most prevalent, accounting for 53.8% of the 23,680 fund-year observations. In comparison, 16.2% adopt a three-year horizon, 26.7% a five-year horizon, and only 3.3% use a ten-year horizon. These figures stand in sharp contrast to corporate executive compensation, which is typically tied to long-term performance (Edmans et al. (2017)).

We are only able to identify manager evaluation horizons for 1,028 funds in 2005–2006, when disclosure was first mandated. The number of funds that disclose manager evaluation horizons in our sample increases to 2,189 in 2007. Fewer funds report short evaluation horizons in 2005-2006, comprising 42.9% of disclosures. Since 2007, the 1-year horizon has consistently exceeded 50%, rising from 53.3% in 2007 to 55.1% in 2018. Over the same period, the adoption rate of the three-year horizon fell from 21.0% to 9.0%, while the 5-year and 10-year horizons rose from 22.9% to 32.2% and 2.7% to 3.8%, respectively.

Table 2 reports descriptive statistics of fund characteristics and returns at the fund-month level. Panel A summarizes key characteristics of the sample funds. The average fund is 14.9 years old, manages $1.7 billion in assets, has an annual turnover ratio of 69.9%, and charges an annual expense ratio of 1.1%. 21.1% of fund assets originate from DC retirement accounts. We note however that our DC ratio variable is only available for a small subsample.

The average fund in our sample earns a gross monthly return of 0.79% and a net return of 0.71%. The average monthly excess return is -0.13% when benchmarked against the fund's self-designated index from the Morningstar database, -0.012% relative to the characteristics-based benchmark portfolios constructed by Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004), and -0.079% relative to the Carhart (1997) four-factor model. We also calculate each fund's buy-and-hold abnormal returns (BHARs) in the subsequent 12-, 36-, and 60-month periods, relative to the BHARs of its self-designated index. The average BHARs are -0.7%, -7.4%, and -21.5% for the 12-, 36-, and 60-month holding horizons, respectively. Variable definitions are provided in Table B.1 of the Internet Appendix.

In Panel B of Table 2, we categorize the funds into "long-horizon" and "short-horizon" categories and compare their characteristics and performance. A "short-horizon" (SH hereafter) fund has a manager evaluation horizon of one year, while a "long-horizon" (LH hereafter) fund has a manager evaluation horizon exceeding one year. We follow this classification for the rest of the analyses in the paper. The results indicate that, compared to SH funds, LH funds tend to be larger, older, and have lower turnover and expense ratios. Additionally, LH funds manage a greater proportion of DC plan assets than do SH funds, suggesting that they serve a more patient and stable investor base. This is consistent with the fact that investors in DC plans are generally more inclined to invest their retirement savings with a long-term focus. LH funds also deliver higher returns than SH funds. On average, LH funds outperform SH funds by 0.085% per month in net returns, 0.076% per month in benchmark-adjusted returns, and 0.051% per month in fund alpha. This outperformance accumulates to a total of 6.2% in terms of BHARs over a five-year holding period.

These univariate results align with the hypotheses discussed earlier. In the next section, we expand our analysis to a multiple regression framework to provide a more comprehensive picture.

3 Effects of Manager Performance Evaluation Horizon

3.1 Manager Evaluation Horizon and Investment Horizon

Our central hypothesis is that compensation contracts with longer performance evaluation horizons shield fund managers from the short-term pressures imposed by investors. As a result, these contracts help realign managers' incentives toward exploiting long-term mispricing and maintaining longer holding periods for portfolio stocks. To test this, we now examine the characteristics of fund holdings and trading behavior to assess whether managers with long-horizon contracts are more inclined to pursue long-term investment strategies.

3.1.1 Portfolio Holding Horizon

We begin by investigating the relationship between a manager's performance evaluation horizon and the holding horizon of the fund's portfolio. We use two proxies for a fund's holding horizon: the portfolio turnover ratio and the holding horizon measure developed by Lan, Moneta, and Wermers (2024). Unlike the portfolio turnover, the fund's holding horizon is not reported, but instead needs to be inferred from portfolio holdings. We follow the methodology of Lan et al. (2024) and calculate the holding period of each stock in a fund's portfolio in a given quarter as the time elapsed since the position was initiated. A fund's holding horizon is the difference between the portfolio-weighted average holding period of all stocks held by the fund minus the average holding horizon of the funds in the same investment style. This adjustment accounts for funds' different investment styles that focus on different pools of stocks. Optimal holding periods are likely to vary across fund styles.

We estimate separate regressions for turnover ratio and the portfolio holding horizon measure. Our main explanatory variable is a long-horizon indicator variable (LH), which equals 1 if the fund's manager evaluation horizon exceeds one year, and 0 otherwise. In these tests, we control for (the natural logarithm of) fund size, expense ratio, and fund flow measured at the end of the previous month. Additionally, funds that offer share classes with load fees are known to be associated with patient capital (Gomez et al. (2024)). To account for these patient investors, we include the indicator variable *I(load)* in our regression as an additional control variable. We also include fund style and year-month fixed effects. Finally, in the regression of the fund's portfolio holding horizon, we also control for lagged turnover. Standard errors are two-way clustered by fund and time. The unit of observation is fund-month.

The regression results, reported in Table 3, show that long-horizon funds have significantly lower turnover ratios (columns (1)-(2)) and significantly longer holding horizons. In terms of economic magnitude, the turnover ratio of long-horizon funds is about 5% (=0.035/0.6986) lower than the unconditional mean turnover ratio (see Table 2). Similarly, the holding horizon of long-horizon funds is about 9.8% (=0.283/2.9) longer than the unconditional mean holding horizon of 2.9 years.

In sum, long-horizon funds exhibit lower trading frequency and longer holding periods, supporting our hypothesis that extended manager performance evaluation horizons help shield managers from short-term investor pressure. The somewhat modest economic magnitudes also suggest that our contract-based horizon sorts are different from the revealed horizon sorts (based on turnover ratio and portfolio holding horizon) utilized in previous studies (for example, Lan, Moneta, and Wermers (2024) and van Binsbergen, Han, Ruan, and Xing (2024)). This is consistent with an option-like feature arising from long-horizon contracts, which allow managers to also consider long-horizon investment opportunities. Whether these less-constrained managers end up exploiting short- or long-term mispricings will ultimately depend on the opportunities available to them.

3.1.2 Long Horizon Funds' Trading in Fire-Sale Stocks

To investigate whether funds with long evaluation horizons are more likely to pursue long-horizon arbitrage strategies, we adopt the testing framework proposed by Giannetti and Kahraman (2018). Specifically, we identify securities experiencing periods of long-term mispricing using transitory price shocks caused by mutual fund fire sales. This approach is motivated by the idea that large outflows often force fund managers to liquidate assets, creating significant downward price pressure. Coval and Stafford (2007) demonstrate that stocks affected by fire sales experience sharp, yet temporary, price declines that can persist for several quarters. As a result, trading against flow-induced mispricing represents a long-term profit opportunity, though it may not yield immediate returns in the short term.

A potential concern with using actual fire sales to identify transitory shocks is that mutual fund managers retain discretion over which stocks to sell in response to investor redemptions. To address this issue, we construct two measures of a stock's exposure to fire sales, following prior literature. First, we closely follow the approach in Edmans, Goldstein, and Jiang (2012, EGJ) and Gredil et al. (2022) to construct the implied trade pressure (*MFFlow*). This measure assumes that funds experiencing significant outflows (greater than 5% of assets) scale down their holdings proportionally to existing portfolio weights. Specifically, we begin by calculating the dollar outflow for fund j from the end of quarter $q-1$ to the end of quarter

q as follows:

$$Outflow_{j,q} = -(TNA_{j,q} - TNA_{j,q-1}(1 + r_{j,q})), \tag{1}$$

where $TNA_{j,q}$ is the assets under management of fund $j = 1, ..., m$, in quarter q and r is the net return of fund j in quarter q. In every quarter q, summing only over the m funds for which the percentage outflow ($\frac{Outflow_{j,q}}{TNA_{j,q-1}}$) is greater than 5%, we then construct:

$$MFFlow_{i,q} = \sum_{j=1}^{m} \frac{Outflow_{j,q} * w_{i,j,q-1}}{\text{Volume}_{\text{i,q}}}, \tag{2}$$

where $i = 1, ..., n$ indexes stocks, $Volume_{i,q}$ is the total dollar trading volume of the stock during quarter q, and

$$w_{i,j,q} = \frac{Shares_{i,j,q} * Price_{i,q}}{\text{TNA}_{\text{j,q}}}, \tag{3}$$

is fund j's holdings of stock i as a percentage of fund j's TNA at the end of the quarter.

The second measure of fire sales we employ is the flow induced trade measure (FIT) developed by Lou (2012):

$$FIT_{i,q} = \frac{\sum_j Shares_{i,j,q-1} * flow_{j,q} * PSF_{j,q-1}}{\sum_j Shares_{i,j,q-1}}\ , \tag{4}$$

where $PSF_{i,q-1}$ is the partial scaling factor estimated using regressions of percentage changes in shares of stock i held by fund j, on fund j's flows and the interactions of flows with portfolio-level liquidity and ownership as specified in columns 3 and 7 of Table 2 in Lou (2012). $Flow_{i,q}$ is the capital flow to fund i during quarter q expressed as a percentage of the fund's lagged TNA, and $Shares_{i,j,q-1}$ is the number of shares held by fund j as of the end of the previous quarter.[10]

The two fire-sale measures differ in at least two key respects. First, *FIT* accounts for both fund inflows and outflows, whereas *MFFlow* focuses solely on outflows. Second, *MFFlow*

[10]Appendix A.2 provides additional details regarding the construction of the two measures of fire sales.

scales flow-induced trades by contemporaneous dollar trading volume, while *FIT* does not. The rationale for scaling by dollar volume is that greater market depth can absorb more intense selling pressure with less price impact, *ceteris paribus*. As a result, *MFFlow* may capture more pronounced transitory price shocks.[11] We use both measures in our analysis and find consistent results across them, mitigating concerns that our findings are driven by mechanical artifacts or spurious correlations.

We transform both fire-sale measures into percentile ranks. Each quarter, stocks with *MFFlow* (or *FIT*) values below the 10th percentile are classified as fire-sale stocks. In unreported results, we verify that these identified fire-sale stocks experience significant price declines that subsequently revert to their original levels over the following six to eight quarters. The magnitude of the price pressure observed in our sample is comparable to that documented by Edmans et al. (2012).

We examine whether a fund manager's evaluation horizon affects fund trading behavior by using the regression model of Giannetti and Kahraman (2018). For all fire-sale stocks identified above, we estimate the following model:

$$\Delta shares(q+k)_{i,s,q} = \alpha + \beta_1 LH_{i,q} + \beta_2 X_{s,q} + \beta_3 X_{i,q} + \beta_4 X_q + \epsilon_{i,s,q}$$

where q is the quarter the stock becomes a fire-sale stock, k is the quarter around quarter q, ranging from -2 to $+3$, and the dependent variable is the change in the number of shares held by fund i in fire-sale stock s over two adjacent quarters, scaled by the stock's total number of shares outstanding. Recall that LH is a indicator variable that takes the value of one if the fund manager's evaluation horizon in the compensation contract is greater than one year (i.e., the fund is a long-horizon fund), and zero otherwise. Following Giannetti and Kahraman (2018), the $X_{s,q}$ and $X_{i,q}$ capture stock and fund characteristics. The stock characteristics

[11] On the other hand, Wardlaw (2020) argues that scaling by contemporaneous volume may make *MFFlow* mechanically related to returns in the event quarter. Importantly, *FIT* is not subject to this standardization concern and Lou (2012) finds that mutual fund sales generate transitory price pressure that subsequently reverses.

include illiquidity (ILLIQ), return momentum, size, idiosyncratic volatility over the past two years (VOL), and book-to-market ratio (BM); the fund characteristic includes fund size as measured by the natural logarithm of the fund's TNA (logTNA). We also control for time fixed effects and cluster standard errors by fund and by time.

Panel A of Table 4 presents the regression results for fire sale stocks identified using the implied trade pressure measure *MFFlow*. The results reveal that long- and short-horizon fund managers make similar trades in fire-sale stocks in the two quarters prior to the stock becoming a fire-sale stock. However, during the two quarters after the stock becomes a fire-sale stock, long-horizon managers take advantage of the flow-driven mispricing opportunities and add more fire-sale stocks to the portfolio than do short-horizon managers. To gauge the extent of differential trading behavior in an economically meaningful way, we also standardize the dependent variable using the standard deviation of all holdings trades of short- and long-horizon funds. This standardization indicates that over two quarters after the fire sale event, the additional purchase of a long-horizon fund is 3 to 4 percent of a standard deviation larger than that of a short-horizon fund. Long-horizon funds' purchases of fire-sale stocks last for two quarters and become statistically insignificant in the third quarter after the stock becomes a fire-sale stock.

To conserve space, we present the regression results for fire-sale stocks based on the FIT measure in Table A.1 in the Appendix. These results are qualitatively consistent with those obtained using the implied trade pressure measure *MFFlow*.

Next, in Panel B of Table 4, we focus on the quarter immediately following the fire-sale event and examine the characteristics of fire-sale stocks favored by long-horizon fund managers. The working hypothesis is that trading differences between long- and short-horizon funds should be more pronounced for fire-sale stocks with higher arbitrage risk (Shleifer and Vishny

(1997)). For instance, Giannetti and Kahraman (2018) suggest that small-cap stocks and those with high idiosyncratic volatility tend to be associated with elevated arbitrage risk.

The first two columns of Panel B provide evidence consistent with these economic priors. In column (1), the coefficient on the interaction between *LH* and *Size* is negative and statistically significant, suggesting that the difference in trading behavior between long- and short-horizon funds is more pronounced for smaller fire-sale stocks. This aligns with the idea that smaller stocks carry higher arbitrage risks. Similarly, if high idiosyncratic volatility signals greater arbitrage risk (Pontiff (2006)), we expect short-horizon funds to shy away from trading against mispricing in such stocks, while long-horizon funds may be more willing to do so. The coefficient on the interaction between *LH* and *Vol* in column (2) supports this hypothesis. In the remaining columns, we explore additional stock characteristics—including illiquidity, book-to-market ratio, and return momentum—but find no significant relationship between these characteristics and the fire-sale trading activity of long-horizon funds.

In Panel C of Table 4, we also focus on the quarter immediately following the fire-sale event and examine fund characteristics that could affect the fund's incentives to purchase fire-sale stocks. We hypothesize that, *ceteris paribus*, a long-horizon fund is less incentivized to exploit long-term mispricing opportunities if its flows are more sensitive to short-term fund performance and thus yield greater outflow pressure from short-horizon investors (Sirri and Tufano (1998)). To test the hypothesis, we add fund flow-performance-sensitivity (*FPS*) and its interaction term with *LH* to the regression, and observe negative and statistically significant coefficients on the interaction term in the regressions for all funds (column (1)).

One potential concern with our results is that the difference in trading patterns across short- and long-horizon funds is simply due to short-horizon funds experiencing large outflows. To take into account the effect of financial slack, we re-estimate our model only with nondistressed funds that are not facing large outflows. These results are reported in columns (2) and (3) in

Panel C. When we exclude funds in the bottom 10th percentile of the flow distribution, the results are still consistent with our hypothesis.

These results suggest that fund managers with longer evaluation horizons are more inclined to engage in long-horizon arbitrage strategies by purchasing fire-sale stocks, particularly those with higher arbitrage risk. This behavior contrasts with that of short-horizon managers, who are less likely to exploit such opportunities. Our findings are consistent with those of Giannetti and Kahraman (2018), who show that closed-end funds—insulated from the redemption pressure of short-horizon investors—are more likely than open-end funds to buy fire-sale stocks.

3.1.3 Equity Term Structure and Long-Horizon Risk Loadings

Our results so far show that managers with long-horizon evaluation contracts hold securities longer and are more likely to engage in long-horizon opportunities as captured by fire-sale events. In this section we show that long-horizon funds load more heavily on long-term risk. Since long-term risk is not directly observable, we infer it from the equity term structure using the methodology of Gonçalves (2021).

The pioneering work of Merton (1973) on intertemporal CAPM (ICAPM) accounts for the trade-offs facing, in particular, long-term investors, and takes into account the hedging demand arising from varying investment opportunities. In a recent paper, Gonçalves (2021) argues that the full term structure of equity-strip expected returns fully summarizes investment opportunities at different horizons. In particular, the two state variables that describe investment opportunities over one year or longer, $N_{dr}^{(1)}$ and N_{dr}, respectively, jointly describe the term structure of discount rate news (i.e. term structure of equity-strip expected returns.) He develops a methodology to uncover the equity strip returns and shows that equity strips can be used as state variables capturing investment opportunities as in the framework of ICAPM.

We follow the methodology of Gonçalves (2021) using our sample of mutual funds as test assets and decompose fund returns into a portfolio of equity strip returns. The decomposition requires information on dividends paid out by funds. While daily dividend reports are available for funds, the data are known to be noisy, with a sum of the daily reported dividends often exceeding dividends reported in the annual report. Therefore, we follow Harris, Hartzmark, and Solomon (2015), and use the annual amount from summary reports from CRSP. We assume that the fraction of the annual amount paid on each day is in proportion to the fraction of the total daily sum reported in the daily file.

Specifically, we decompose fund returns $\tilde{r}_t$ into a portfolio of equity strip returns, $\tilde{r}_t^{(h)}$ over different horizons h:

$$\tilde{r}_t = \sum_{h=1}^{\infty} w^{(h)} \tilde{r}_t^{(h)}. \tag{5}$$

The equity strip returns over horizon h stem from three sources,

$$\tilde{r}_t^{(h)} = \widetilde{\Delta d_t} + N_{g,t}^{(h-1)} - N_{dr,t}^{(h-1)}, \tag{6}$$

where $\widetilde{\Delta d_t}$ is dividend growth, $N_{g,t}^{(h-1)}$ is news about future dividend growth for the remaining $h-1$ years, and $N_{dr,t}^{(h-1)}$ is news about future discount rates for the remaining $h-1$ years. Following Gonçalves (2021), we assume that these equity strip returns $\tilde{r}_t^{(h)}$ are generated by the residual vector $\tilde{z}_t$ of the vector auto-regressive model (VAR),

$$z_t = \Phi_0 + \Phi_1 z_{t-1} + \tilde{z}_t. \tag{7}$$

The vector z_t consists of the following state variables,

$$z_t = \begin{bmatrix} r_f(t) & xr(t) & dp(t) & ty(t) & ts(t) & cs(t) & vs(t) \end{bmatrix}$$

where $r_f(t)$ is the return on the one-month Treasury bill, $xr(t)$ is the return of the fund in excess of the risk-free rate, $dp(t)$ is the dividend yield defined as the natural logarithm of aggregate dividends over the normalized price of the fund, $ty(t)$ is the one-year Treasury yield, $ts(t)$ is the term spread defined as the yield difference between the 10-year and 1-year treasury securities, $cs(t)$ is the credit spread defined as the yield difference between Moody's corporate Baa and Aaa bonds, and $vs(t)$ is the value spread defined as the log difference between the book-to-market ratios of the value and growth portfolios formed based on small stocks. All flow variables—dividend growth and returns—are deflated using the Consumer Price Index. We use ordinary least squares to estimate the transformation matrix Φ in Eqn. (7). Finally, we estimate the equity strip returns, $\tilde{r}_h^{(h)}$ by using the transformation matrix Φ, the residual state vector $\tilde{z}_t$ (Eqn. (7)), and horizon h.

$$\tilde{r}_t^{(h)} = \mathbf{1}'_{\Delta d}\tilde{z}_t + \mathbf{1}'_{\Delta d} \cdot B^{(h-1)}\tilde{z}_t - \mathbf{1}'_r \cdot B^{(h-1)}\tilde{z}_t = \left[\mathbf{1}'_{\Delta d} + (\mathbf{1}'_{\Delta d} - \mathbf{1}'_r) \cdot B^{(h-1)}\right]\tilde{z}_t, \tag{8}$$

where

$$B^{(h)} = \left(\Phi_1 - \Phi_1^{h+1}\right)\left(\mathbf{I}_\Phi - \Phi_1\right)^{-1}. \tag{9}$$

The weights $w^{(h)}$ in Eqn. (5) are estimated by projecting the fund returns $\tilde{r}_t$ onto the h-year equity strip returns. To be consistent with the decomposition of the returns, we normalize these weights so that they sum to one.

Table 5 presents the cumulative loadings of long- and short-horizon funds on dividend strips. Short-horizon funds exhibit significantly higher loadings on near-term risks, while long-horizon funds are more exposed to long-term risk. Specifically, long-horizon funds have a cumulative loading of 0.224 on short-term (one- to five-year) dividend strips, compared to 0.275 for short-horizon funds—a difference that is statistically significant at the one percent level. Figure 2 illustrates the loadings on dividend strips for each of the future ten years, showing that short-horizon funds consistently load more on short-horizon risks.

Furthermore, we estimate the average duration of long- and short-horizon funds using the methodology of Gonçalves (2021). We find that long-horizon funds have an average duration approximately 8% higher than that of short-horizon funds, and this difference is statistically significant. These findings reinforce the view that longer evaluation horizons encourage fund managers to take on greater exposure to long-horizon risks.

3.2 Manager Evaluation Horizon and Fund Performance

The results in the previous section suggest that managers evaluated on long-horizon performance criteria are more likely to invest in long-term opportunities. Long-horizon contracts alleviate investment constraints by reducing short-term pressures, thereby expanding the opportunity set available to fund managers. Short-horizon contracts, in contrast, limit peer managers to opportunities with short-term payoffs, which are also less scalable (van Binsbergen, Han, Ruan, and Xing (2024)). Therefore, we expect long-horizon managers to outperform their short-horizon counterparts. We examine this hypothesis, first by looking at performance differences of portfolios of stocks favored by long horizon funds and short horizon funds, respectively, and second by comparing the performance of long and short horizon funds.

Accordingly, each month, we first sort stocks into quintiles based on their ownership by long-horizon funds. Stocks with the lowest ownership are placed in the first quintile (Q1), while those with the highest ownership fall into the fifth quintile (Q5). For each quintile, we compute value-weighted returns up to five years into the future and then estimate portfolio alphas relative to the Fama-French three-factor model.

Figure 3 plots the alphas for Q1 and Q5 stocks over the subsequent five years. Stocks in Q5 consistently outperform those in Q1 across the entire period. Specifically, Q1 stocks exhibit persistently negative alphas, whereas Q5 stocks maintain positive alphas throughout. The alpha spread between Q5 and Q1 supports the notion that long-horizon contracts alleviate investment constraints and enhance fund performance.

We next evaluate the performance of long- versus short-horizon funds using a comprehensive set of fund performance measures. We first evaluate funds using various performance metrics calculated monthly. We then turn to buy-and-hold abnormal returns (BHARs) calculated over one-, three-, and five-year horizons.

Our monthly measures include the fund's monthly net-of-fee returns and corresponding monthly benchmark-adjusted performance metrics. The first benchmark-adjusted measure is the fund's return in excess of its self-declared benchmark index, obtained from Morningstar (hereafter, "benchmark-adjusted return"). The second is the fund's alpha relative to the Carhart (1997) four-factor model, with factor loadings estimated over the prior 24 months ("Alpha").

Additionally, we construct benchmark-adjusted fund returns following the approach of Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004) ("DGTW-adjusted return" hereafter). Following these studies, we compute the value-weighted monthly returns of the portfolios sorted on size, book-to-market (BM), and momentum characteristics. A stock's DGTW-adjusted return is its monthly return in excess of the return of the size/BM/momentum portfolio to which the stock belongs. A fund's DGTW-adjusted return is the value-weighted DGTW-adjusted returns of the stocks held by the fund. Since the DGTW-adjusted returns are based on the stocks in the fund's portfolio, fund fees are not included in calculating these returns.

Finally, the BHAR metrics over one-, three-, and five-year horizons are defined as the difference between the fund's net-of-fee buy-and-hold return and the corresponding return on its benchmark index.

The results using the monthly performance measures are reported in columns 1-4 of Table 6. We regress each monthly performance measure on the long-horizon indicator variable (LH), which is our explanatory variable of interest. The regressions also include (the natural logarithm of) fund size, turnover, expense ratio, net fund flow - all measured at the end of the prior month, - controls for whether the fund offers a load share class, and fund style and year-month fixed effects. Standard errors are two-way clustered by fund and time, and the unit of observation is fund-month. These model specifications mirror those in Table 3.

The table shows that the coefficient estimate on LH is positive and statistically significant for all model specifications. Economically, Columns (1)-(3) indicate that long-horizon funds outperform short-horizon funds by 54 basis points per month in net returns, 47 basis points per month in benchmark-adjusted returns, and by 28 basis point per month in alpha. Furthermore, Columns (5)-(7) indicate that cumulatively, this outperformance translates to 2.30%, and 4.10% over the 3- and 5-year windows, respectively, in terms of BHARs.

These results align with prior studies that consistently find that mutual funds following long-horizon investment strategies outperform those that focus on short-term opportunities (e.g., Cremers and Pareek (2016), van Binsbergen et al. (2024), van Binsbergen et al. (2025), and Lan et al. (2024)). These papers classify funds into those that invest in short- vs long-horizon opportunities using the length of the fund's holding period of its portfolio stocks (or, alternatively, the turnover of the fund). As we argue above, our horizon sorts are different from those based on the length of funds' investments. Although we show that managers with long-horizon contracts are, on average, more likely to engage in long-term arbitrage and load more on long-run risk, whether these less-constrained managers end up exploiting short- or long-term mispricings will ultimately depend on the opportunities available to them.

To shed more light on our results relative to the existing literature, we re-estimate the fund performance regressions by adding the fund's holding horizon at the end of the previous month as an additional explanatory variable. Note that we already control for the fund's lagged turnover ratio in the regressions reported in Tables 6. The results, reported in Table A.2 in the Appendix, reveal that managers facing long-horizon performance evaluations continue to outperform those with short-horizon contracts after adding the new control. The finding suggests that the outperformance of funds with long manager evaluation horizons cannot be solely attributed to their holding horizons or lower turnover ratios.

3.3 Skill vs. Incentive

The results so far show that funds with longer manager evaluation horizons are more likely to pursue long-horizon mispricings and perform better than short-horizon funds. In this section we provide evidence that our results are unlikely to be driven by unobserved heterogeneity or reverse causality. Rather, they suggest that long-horizon contracts incentivize managers to exploit long-term investment opportunities, resulting in better performance.

To do so, first, we study the effects of long-horizon contracts in samples of long- and short-horizon funds matched on important fund characteristics. Second, we control for (lead) manager-fixed effects to alleviate the concern that unobserved manager characteristics drive the results. Third, we study across-family fund mergers, after which fund managers' evaluation horizons may change. Lastly, we show that managers' career outcomes, such as promotions or demotions, are related to their performance over the contract evaluation horizon.

3.3.1 Matched Samples

A potential concern is that long-horizon funds are different from short-horizon funds. While we cannot exclude the possibility that there are some differences along some unobserved dimensions, to mitigate this concern, we match funds on important observable characteristics. Specifically, for each fund with a long evaluation horizon, we find an observationally similar fund with a short horizon. The matching is based on size, age, expense ratio, turnover ratio, fund flows, and fund performance in the previous month within the same investment style and the same year. We use the 2-digit CRSP fund objective codes to define the funds' investment style. We identify a matching short-horizon fund based on two matching approaches. The first approach minimizes the Gaussian distance of fund characteristics, while the second approach is based on the fund's propensity to adopt a long evaluation horizon.

We re-estimate the regressions in Table 6 for the each of the two matched samples. The estimation results, tabulated in Table A.3 in the Internet Appendix, show that the results based on the full sample remain qualitatively unchanged in both matched samples.

3.3.2 Manager Fixed Effects

An alternative explanation for our performance results is managerial skill. Do skillful managers with more bargaining power self-select into long-horizon contracts? To rule out this alternative channel, we re-estimate the regressions in Tables 3 and 6, adding manager fixed effects as additional control variables. A potential hurdle of implementing this approach is that there has been a growing trend toward team management in the mutual fund industry, as documented by Dass, Nanda, and Wang (2013) and Patel and Sarkissian (2017). Therefore we rely on the hierarchy structure of team management, which implies the existence of a central decision maker, i.e. a lead manager. Using Morningstar manager history data, we measure the tenure of each manager in a fund, and designate the manager with the longest tenure record as the lead manager for the fund. The results using lead manager fixed effects, reported in Table A.4 in the Appendix, show that the baseline results remain qualitatively unchanged. These results alleviate the concern that the baseline results are driven by unobserved manager characteristics.

3.3.3 Across-Family Fund Mergers and Manager Evaluation Horizon

To mitigate the concern that well performing funds select into longer horizon contracts, we exploit across-family mutual fund merger events. Jayaraman et al. (2002) show that across-family fund mergers are more likely to occur for strategic reasons, rather than because of poor performance or large expense ratios prior to the mergers. For instance, small families may engage in across-family mutual fund mergers to bolster the potential choices of funds and investment objectives in their fund lineup. Such product differentiation seems to drive the market share of fund families (Khorana and Servaes (2012)). In contrast, small funds with poor performance are more likely to be targets of within-family fund mergers. Therefore, we exploit fund mergers as a plausibly exogenous shock to manager evaluation horizons and examine the effect of changes of fund manager evaluation contracts around across-family fund mergers.

A fund family often adopts a uniform manager evaluation horizon across its equity funds. To idenitfy fund mergers across families, we closely follow the approach of McLemore (2019) and match a target fund to its acquiring fund from the merger event using a delist code of *M* from the CRSP mutual fund database. Mergers within the same fund family or mergers among share classes of the same fund are excluded from our analysis, resulting in 167 observations in units of fund-quarter during our sample period.

To address concerns that mergers may not be entirely exogenous, we implement a difference-in-differences (DiD) research design. Treated funds are those whose manager evaluation horizon increases from one year to more than one year following the merger. Control funds are those whose evaluation horizon remains unchanged after the merger. We match each treated fund to three control funds based on important fund characteristics, including fund size, turnover ratio, expense ratio, and fund flow based on a three-year window prior to the merger using the Gaussian distance matching rule.[12] We then provide analyses based on the three years before and after each of the merger event.

Table 7 presents the DiD regression results. The dependent variables are turnover ratio and holding horizon in Columns (1)-(2), and fund performance measures in Columns (3)-(9).

[12]We note that the ideal case would be where the treated funds retain the same managers after the merger. Such cases are rare, however, and constitute a small fraction of our sample.

The key explanatory variable is labeled *DiD*, which captures the interaction between the treatment indicator and the post-merger indicator. The table shows that the coefficient estimate is negative and statistically insignificant in column (1), where the dependent variable is the turnover ratio, but positive and statistically significant in column (2), where the dependent variable is the holding horizon. Across the seven fund performance metrics, the coefficient on the interaction term is positive in all specifications and statistically significant in most cases.

Taken together, these results reinforce the causal interpretation that extending manager evaluation horizon leads to longer portfolio holding periods and improved fund performance.

3.4 Manager Evaluation Horizon and Manager Turnover

The preceding analysis suggests that manager evaluation horizon has real effects on fund managers' portfolio decisions and performance, implying that the stated evaluation horizon disclosed in the SAI document is not merely symbolic, but binding. In this section, we examine whether funds' manager turnover decisions are consistent with this view—that is, whether performance is assessed over the disclosed evaluation horizon when making manager turnover decisions.

We examine turnover via manager promotions or demotions at the fund level. To do so, we begin with the Morningstar manager history data. We first identify manager promotions or demotions using multiple criteria, following the methodology in the literature (Evans (2009), for instance). *Promotion* is a binary variable that takes the value of 1 if one or more of the following occur: (1) the manager moves to a fund with larger assets, (2) the manager becomes the lead manager of a new fund with similar or greater assets, or (3) the manager takes on the management of a larger number of funds. *Demotion* is a binary variable that takes the value of 1 if one or more of the following occur: (1) the manager moves to a fund with smaller assets, (2) the manager is no longer the lead manager in the new fund, or (3) the manager takes on the management of a smaller number of funds. In cases where both *Promotion* and *Demotion* would take the value of 1, we set *Demotion* to be 0. We then aggregate individual manager turnover data at the fund level by taking the percentage of promotions (or demotions) of the managers at the fund.[13] To exclude potential voluntary retirement, we remove manager ('demotion') moves where the manager's tenure in the industry exceeds 30 years.

We estimate linear probability models in which the dependent variable is *Promotion* (or *Demotion*) at the fund level in year t. The main explanatory variable is the interaction between the long-horizon indicator (LH) and fund performance. The performance variable *High cum HPR (t-k,t)* equals 1 if the fund's buy-and-hold return over the past k years is above the cross-sectional median, and 0 otherwise. The performance variable *Low cum HPR (t-k,t)* takes the value of 1 if the fund's buy-and-hold returns over the past k years is below the median of the distribution. We also include our main variable LH and the control variables from our baseline regression models.

Columns (1)-(3) of Table 8 show the results of the promotion analysis, while Columns (4)-(6) show the corresponding results for demotions. Columns (1) and (4) use performance over the past one year (i.e., $k = 1$), Column (2) and (5) use a two-year window, and column (3) and (6) a three-year window. While promotions are positively correlated with performance at all three windows, demotions are positively correlated only with poor performance at the longer horizon, as seen from the coefficient estimate of the interaction term between LH and the performance dummy *Low cum HPR (t-3,t)* in Column (6). These results suggest that for funds with long evaluation horizons, turnover decisions tend to be more closely tied to long-term, rather than short-term, performance, providing further support for the binding nature of evaluation horizons.

[13]We also perform the analysis by defining the manager promotion (or demotion) variable to be one if at least one manager is promoted (or demoted). The results are qualitatively similar and are not reported for brevity.

3.5 Which Funds Use Long-Horizon Evaluation Contracts?

Our results thus far suggest that long-horizon contracts are effective in removing short-run performance constraints and lead to better fund performance. This finding echoes a large corporate finance literature which argues that long-horizon compensation contracts curtail CEO short-termism in nonfinancial firms and incentivize them to invest in long-term projects.

A natural follow-up question is why these contracts are not adopted by all funds in the mutual fund industry. We argue in the Introduction that long-horizon contracts do not directly shut off the short-term funding pressure imposed by investor withdrawals. They simply insulate the manager from such pressure thereby restoring the incentives to focus on long-horizon opportunities.

Because the cost of investor outflows ultimately falls on the fund and its family, only certain types of funds (or fund families) may be in a position to offer long-horizon contracts. We hypothesize that such contracts are more likely to be adopted by two categories of funds: (1) those with a more patient investor base, and (2) those with greater organizational resources to absorb short-term liquidity shocks.

To test these hypotheses, we examine various proxies for investor patience and organizational resources. Our first proxy for patient capital is flow-performance sensitivity (FPS), estimated using a 24-month rolling regression of monthly fund flows on the fund's average monthly return over the previous 12 months.[14] A lower FPS implies that fund investors are less sensitive to short-term performance, and hence more patient. The second proxy for patient capital is the fraction of assets from DC retirement plan investors, who typically exhibit long investment horizons (Sialm and Starks (2012)).[15] Following the previous literature, we obtain data on DC assets from P&I. P&I data are based on voluntary surveys that

[14] Following Giannetti and Kahraman (2018), we winsorize fund flows at the 2.5% level.

[15] These two variables – FPS and DC assets – are shown to be not positively correlated due to the actions of the plan sponsors. (Sialm and Starks (2012))

query managers on the proportion of DC assets in the fund's asset pool. For this reason, the number of participating funds is somewhat limited, restricting our sample size in models that use the DC assets measure.

We also consider the availability of liquidity management resources in the fund family, that is, whether the fund family can provide a liquidity buffer against temporary liquidity shocks. In this context, Agarwal and Zhao (2019) examine the interfund lending program (ILP), which is a liquidity sharing arrangement. Through ILP, affiliated funds can borrow from other funds within the fund family to meet liquidity needs that arise from sudden investor redemptions.

We collect information on ILP's from Form N-CEN filings. Since these filings only became available at the end of our sample period (2018), the relevant sample is limited. To mitigate the small sample size, we follow Agarwal and Zhao (2019) and also instrument the availability of ILP's using the number of money market funds (MMFs) as a fraction of the total number of funds within the family. Fund families with more MMFs should have a more stable liquidity basis and are better equipped to facilitate the liquidity needs of the funds in the family.

Table 9 reports the results from linear probability models, where the dependent variable equals 1 if the fund adopts a long evaluation horizon. The key explanatory variables are the proxies for patient capital and internal resources available within the family. Consistent with our hypothesis, we find that long-horizon contracts are more likely to be adopted by funds that display a lower FPS and have a higher portion of DC assets. Similarly, the availability of an ILP within the family is an important determinant of whether managers are evaluated based on long-horizon performance, as shown in Column (4). As mentioned, this analysis is limited to 2018, the year when Form N-CEN was initiated. However, as Agarwal and Zhao (2019) show, the capital for the ILP is likely supplied by MMFs within the family. Accordingly, Column (3) confirms that the presence of MMFs in the family is also an important determinant of long-horizon contracts.

The additional explanatory variables included in Panel B of the table provide further support. For example, Gomez et al. (2024) show that funds with load fees are associated with investors' long-term capital commitment to the funds. Consistent with this view, we find that the coefficient estimates for *I(load)* are all significantly positive. These findings support the view that both investor patience and organizational resources play important roles in determining the adoption of long-horizon evaluation contracts.[16]

Finally, it is interesting to note that we consistently find a negative relation between manager tenure and contract horizon. In the sense that managers with longer tenures (e.g., with long survival rates) are more likely to be skilled, these results provide further evidence that contract horizon does not simply proxy for skill. Instead, in addition to isolating managers from short-term funding pressure, long-horizon evaluations may also mitigate short-termism due to career concerns (van Binsbergen et al. (2025)).

4 Conclusion

Investors often rely on short-term performance signals to evaluate mutual funds. When investors vote with their feet based on recent performance, funds face the risk of withdrawals if they perform poorly in the short term. This short-sighted funding pressure discourages managers from investing in long-horizon mispricings which risk incurring losses in the short run before converging to their future payoffs (Stein (2005) and Shleifer and Vishny (1997)).

We argue that fund families can insulate managers from this funding pressure by offering them compensation contracts that are tied to long-term fund performance. We show that these contracts are effective in restoring managers' incentives to consider long-term opportunities.

[16]We replicate this analysis at the fund family level in Table A.5 of the Appendix and find similar results.

Our results show that managers with long-horizon contracts are more likely to undertake long-term investments and outperform their constrained peers.

Since long-horizon pay does not shut off the funding pressure, it simply insulates the manager from it, not all families can offer these contracts. We find that bonuses that are tied to long-term fund performance are more prevalent among funds and families that are older, larger, and have a more diversified asset base. That is, among funds that are likely to be more reputable. These families are also likely to have more resources and flexibility to provide a buffer against temporary liquidity shocks to their member funds.

Importantly, the occurrence of long-horizon contracts is also strongly related to the patience of the fund's/family's investor clientele. This is consistent with the idea that for funds/families that cater to patient clients, offering these contracts is less costly. Specifically, we find that funds with higher flow-performance are less likely to pay managerial bonuses that are tied to long-horizon fund performance. In contrast, funds that manage larger defined contribution retirement assets are more likely to offer these contracts.

References

Agarwal, V. and H. Zhao (2019). Interfund lending in mutual fund families: Role in liquidity management. *The Review of Financial Studies 32*(10), 4079–4115.

Amihud, Y. (2002). Illiquidity and Stock Returns: Cross-section and Time-series Effects. *Journal of Financial Markets*, 31–56.

Bai, J., L. Ma, and K. Mullally (2024). What determines mutual fund managers' compensation? evidence from u.s. administrative earnings data. *Working Paper*.

Barber, B. M., T. Odean, and L. Zheng (2003). Out of sight, out of mind: The effects of expenses on mutual fund flows.

Carhart, M. M. (1997). On the persistence of mutual fund performance. *Journal of Finance 52*, 57—82.

Christoffersen, S. K. and M. Simutin (2014). On the demand for high-beta stocks: Evidence from mutual funds. *Working Paper*.

Coval, J. and E. Stafford (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics 86*, 479—512.

Cremers, M. and A. Pareek (2016). Patient capital performance. *Journal of Financial Economics 122*, 288–306.

Cuoco, D. and R. Kaniel (2011). Equilibrium prices in the presence of delegated portfolio management. *Journal of Financial Economics 101*(2), 264–296.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers (1997). Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance 52*, 1035—58.

Dass, N., V. Nanda, and Q. Wang (2013). Allocation of decision rights and the investment strategy of mutual funds. *Journal of Financial Economics 110*(1), 254–277.

Du, W., X. Cen, L. Kogan, and W. Wu (2025). Fund flows and income risk of fund managers. *Working Paper*.

Edelen, R. M. (1999). Investor flows and the assessed performance of open-end mutual funds. *Journal of Financial Economics 53*, 439—-466.

Edmans, A., X. Gabaix, and D. Jenter (2017). Dynamic ceo compensation. *In B. Hermalin and M. Weisbach (Eds.) The Handbook of the Economics of Corporate Governance 1*, 383–539.

Edmans, A., X. Gabaix, T. Sadzik, and Y. Sannikov (2012). Dynamic ceo compensation. *Journal of Finance 67*, 1603–1647.

Edmans, A., I. Goldstein, and W. Jiang (2012). The real effects of financial markets: The impact of prices on takeovers. *Journal of Finance 67*, 933–971.

Evans, R. B. (2009). Does alpha really matter? evidence from mutual fund incubation, termination, and manager change. *Working paper*.

Giannetti, M. and B. Kahraman (2018). Open-end organizational structures and limits to arbitrage. *The Review of Financial Studies 31*, 773–810.

Gomez, J.-P., M. P. Prado, and R. Zambrana (2024). Capital committment and performance: The role of mutual fund charges. *Journal of Financial and Quantitative Analysis 59*, 727–758.

Gonçalves, A. S. (2021). Reinvestment risk and the equity term structure. *Journal of Finance 76*, 2153–2197.

Gredil, O. R., N. Kapadia, and J. H. Lee (2022). On the information content of credit ratings and market-based measures of default risk. *Journal of Financial Economics 146*(1), 172–204.

Harris, L. E., S. M. Hartzmark, and D. H. Solomon (2015). Juicing the dividend yield: Mutual funds and the demand for dividends. *Journal of Financial Economics 116*, 433–451.

Hasbrouck, J. (2009). Trading costs and returns for u.s. equities: Estimating effective costs from daily data. *Journal of Finance 64*, 1445–1477.

Hausman, J. (1978). Specification tests in econometrics. *Econometrica 46*, 1251–1271.

Hodor, I. and F. Zapatero (2023). Asset pricing implications of heterogeneous investment horizons. Working Paper.

Hombert, J. and D. Thesmar (2014). Overcoming limits of arbitrage: Theory and evidence. *Journal of Financial Economics 111*, 26–44.

Ibert, M., R. Kaniel, S. V. Nieuwerburgh, and R. Vestman (2018). Overcoming limits of arbitrage: Theory and evidence. *Review of Financial Studies 31*, 715–772.

Jayaraman, N., A. Khorana, and E. Nelling (2002). An analysis of the determinants and shareholder wealth effects of mutual fund mergers. *The Journal of Finance 57*(3), 1521–1551.

Khorana, A. and H. Servaes (2012). What drives market share in the mutual fund industry? *Review of Finance 16*(1), 81–113.

Lan, C., F. Moneta, and R. Wermers (2024). Holding horizon: A new measure of active investment management. *Journal of Financial and Quantitative Analysis 59*, 1471–1515.

Lee, J. H., C. Trzcinka, and S. Venkatesan (2019). Do portfolio manager contracts contract portfolio management? *Journal of Finance 74*, 2543–2577.

Li, C. W. and A. Tiwari (2009). Incentive contracts in delegated portfolio management. *The Review of Financial Studies 22*(11), 4681–4714.

Lou, D. (2012). A flow-based explanation for return predictability. *Review of Financial Studies 25*, 3457–3489.

Ma, L., Y. Tang, and J.-P. Gomez (2019). Portfolio manager compensation in the u.s. mutual fund industry. *Journal of Finance 74*, 587–638.

McLemore, P. (2019). Do mutual funds have decreasing returns to scale? evidence from fund mergers. *Journal of Financial and Quantitative Analysis 54*, 1683–1711.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica 41*, 867–887.

Patel, S. and S. Sarkissian (2017). To group or not to group? evidence from mutual fund databases. *Journal of Financial and Quantitative Analysis 52*(5), 1989–2021.

Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics 42*, 35–52.

Schwarz, C. G. and M. E. Potter (2016). Revisiting mutual fund portfolio disclosure. *Review of Financial Studies 29*, 3519–3544.

Shleifer, A. and R. W. Vishny (1997). The limits of arbitrage. *Journal of Finance 52*, 35–55.

Sialm, C. and L. Starks (2012). Mutual fund tax clienteles. *Journal of Finance 67*, 1397–1422.

Sirri, E. R. and P. Tufano (1998). Costly search and mutual fund flows. *Journal of Finance 53*(5), 1598–1622.

Stein, J. C. (1989). Efficient capital markets, inefficient firms: A model of myopic corporate behavior. *Quarterly Journal of Economics 104*, 655–669.

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

van Binsbergen, J., J. Han, H. Ruan, and R. Xing (2024). A horizon-based decomposition of mutual fund value added using transactions. *Journal of Finance 79*, 1831–1882.

van Binsbergen, J., J. Han, H. Ruan, and R. Xing (2025). Career concerns, short-termism, and real options: The case of delegated money management. *Journal of Finance*, forthcoming.

Wardlaw, M. (2020). Measuring mutual fund flow pressure as shock to stock returns. *Journal of Finance 75*, 3221–3243.

Wermers, R. (2004). Is money really 'smart'? new evidence on the relation between mutual fund flows, manager behavior, and performance persistence. *Working Paper*.

Figure 1: Number of Funds with Different Evaluation Horizons Over Time. This figure plots the number of actively managed domestic equity funds in our sample with different evaluation horizons by year from 2005 to 2018. When a fund reports multiple evaluation horizons, the maximum evaluation horizon is shown. Fund families are required to disclose information about their compensation contracts as of 2005 in the Statement of Additional Information. The disclosure of evaluation horizons in numerical form was less common in the first two years due to the lack of standard disclosure guidelines and was gradually adopted thereafter. For the years 2005 and 2006, evaluation horizons of 4 years have been rounded up to 5 years for 59 funds. Two funds with evaluation horizon of 7 years and one with 8 years have been rounded up to 10 years.

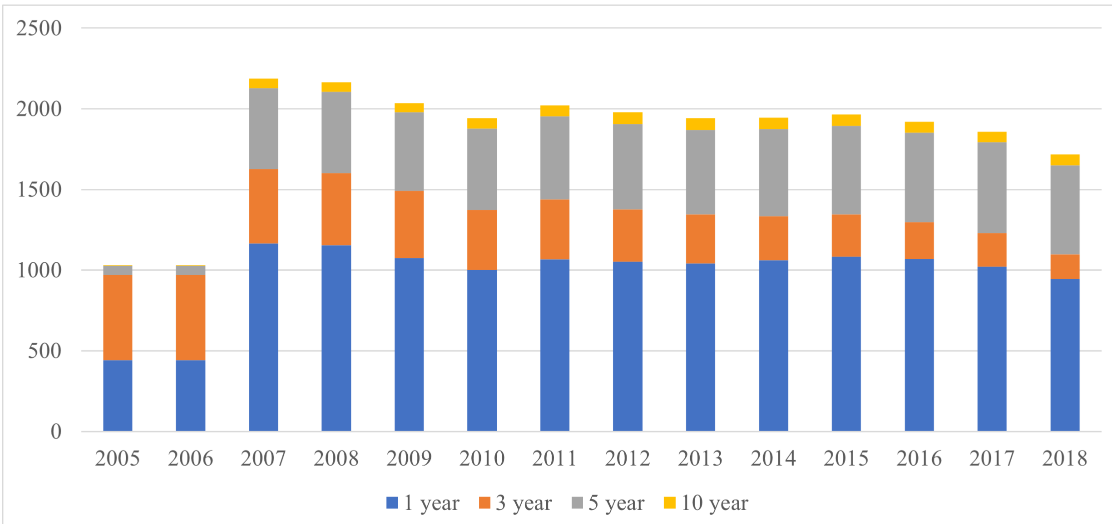

Figure 2: Loadings on the Long and Short Horizon Risk Factors This figure shows the average loadings of fund returns on the long- and short-horizon risks. The loadings for long-horizon funds (LH) are in red and those for short-horizon funds (SH) are in blue. We follow the methodology of Gonçalves (2021) to construct horizon-specific risk factors. For each fund, we find the risk loadings for those risk factors, which are then averaged by the fund's evaluation horizons.

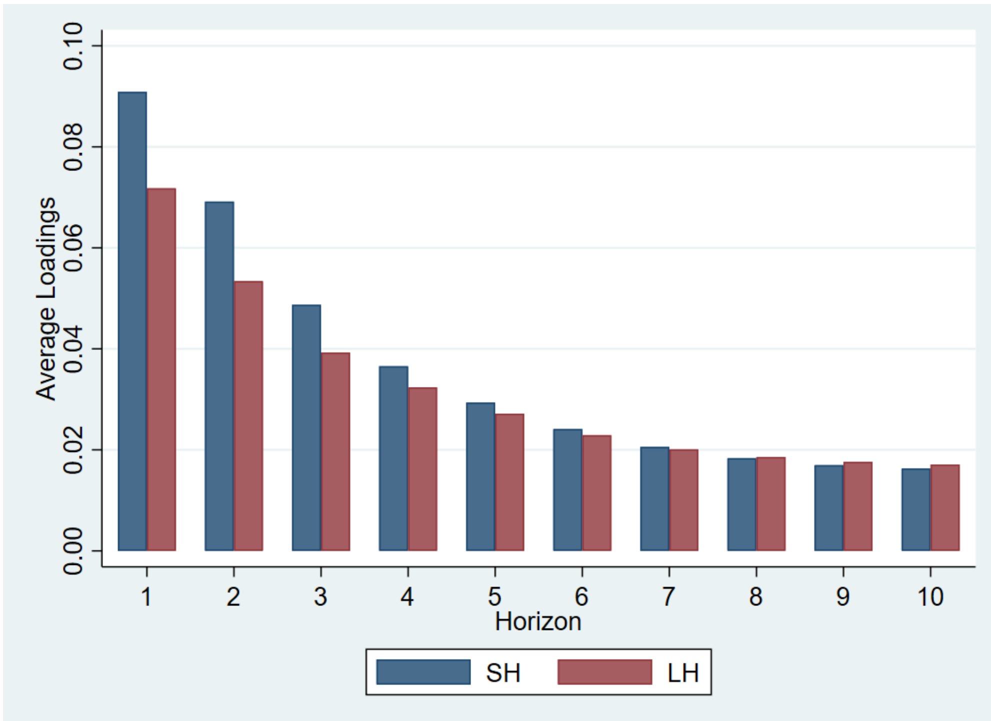

Figure 3: Returns of Stock Holdings by Long-Horizon and Short-Horizon Funds. The graph shows the Fama-French three factor alpha for the constituent stocks held by long- and short-horizon funds. For each stock and each month, we consider the total position of long-horizon funds minus that of short-horizon funds. Each month the stock is placed into quintiles based on this aggregate position difference. A stock in quintile 1 is largely held by short-horizon funds and a stock in quintile 5 by long-horizon funds. We then compute the compound return of these two quintiles over the next 1, 2, 3, 4 and 5 years. To calculate the three factor alpha, we use 24-month rolling windows.

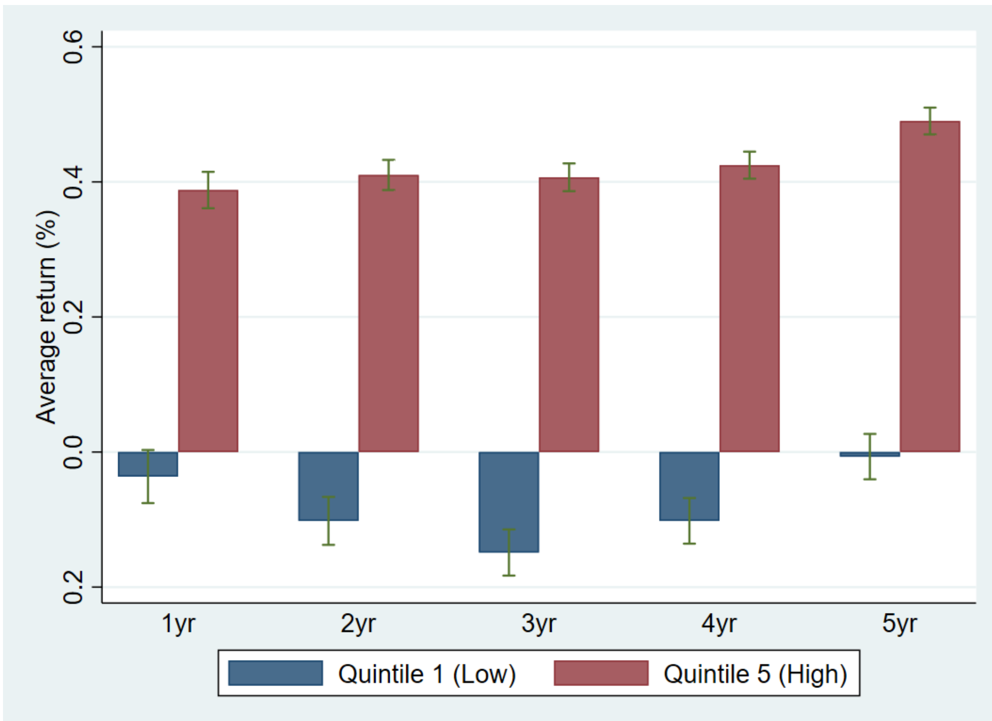

Table 1: Funds with Long and Short Evaluation Horizons. This table shows the number of funds in our sample for a given evaluation horizon by year. We hand collect evaluation horizons for each fund and each year from the Statement of Additional Information. When a fund has multiple evaluation horizons, we take the longest. Our sample includes 2,952 unique U.S. equity mutual funds from 2005 to 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			# funds				Percentage of funds		
Year	# funds	1 year	3 year	5 year	10 year	1 year	3 year	5 year	10 year
2005	1,028	443	528	56	1	42.91	51.90	5.10	0.09
2006	1,028	443	528	56	1	42.91	51.90	5.10	0.09
2007	2,189	1,166	460	501	60	53.27	21.11	22.89	2.74
2008	2,165	1,154	448	503	60	53.3	20.69	23.23	2.77
2009	2,036	1,076	415	487	58	52.85	20.38	23.92	2.85
2010	1,942	1,001	372	506	63	51.54	19.16	26.06	3.24
2011	2,021	1,066	372	515	68	52.75	18.41	25.48	3.36
2012	1,980	1,052	325	528	75	53.13	16.41	26.67	3.79
2013	1,943	1,041	306	523	73	53.58	15.75	26.92	3.76
2014	1,946	1,062	272	542	70	54.57	13.98	27.85	3.6
2015	1,965	1,084	262	550	69	55.17	13.33	27.99	3.51
2016	1,920	1,069	230	554	67	55.68	11.98	28.85	3.49
2017	1,857	1,022	209	563	63	55.04	11.25	30.32	3.39
2018	1,716	945	154	552	65	55.07	8.97	32.17	3.79
All	23,680	12,738	3,827	6,324	791	53.79	16.16	26.71	3.34

Table 2: Descriptive Statistics. This table reports descriptive statistics for our sample. Panel A uses the full sample. In Panel B, we divide our sample into 'long-horizon' (LH) and 'short-horizon' funds (SH). A fund is regarded as a 'long-horizon' fund if its evaluation horizon is longer than one year. Similarly, a fund is considered to be a 'short-horizon' fund when its manager evaluation horizon is one year or shorter. All variables in the table are described in Table B.1 in the Appendix. The DC ratio variable is back-filled. To account for survivorship-bias when calculating the buy-and-hold returns ('BHAR'), when the fund's return is missing, we assume that it is zero. In Panel B, standard errors are clustered by fund.

Panel A.

Variables	Unit	N	Mean	SD	P25	P50	P75
Fund characteristics							
Assets	Bn. dollars	228,267	1.656	5.911	0.075	0.297	1.127
Age	Years	228,265	14.897	11.372	7.499	12.715	18.77
Turn ratio	Percentage	225,734	69.86	76.339	30.000	53.201	87.555
Expense ratio	Percentage	220,953	1.112	0.387	0.900	1.090	1.294
Load	Binary	228,267	0.456	0.498	0	0	1
H-Horizon	Years	210,262	2.913	1.625	1.703	2.604	3.800
Clientele							
DC ratio	Number	42,270	0.211	0.150	0.076	0.188	0.322
Monthly returns (Forward)							
Total returns	Percentage	228,267	0.791	1.688	0.169	1.021	1.689
Net returns	Percentage	228,267	0.706	1.689	0.086	0.936	1.606
Benchmark-adj. returns	Percentage	175,844	-0.131	0.665	-0.371	-0.103	0.148
CS	Percentage	191,488	-0.012	0.455	-0.208	0.005	0.209
4F alpha	Percentage	223,172	-0.079	0.728	-0.391	-0.077	0.242
Buy-Hold returns							
$BHAR_{net,12}$	Percentage	175,070	-0.716	7.085	-3.773	-0.347	2.890
$BHAR_{net,36}$	Percentage	174,823	-7.369	19.837	-16.270	-3.573	4.371
$BHAR_{net,60}$	Percentage	172,061	-21.460	38.749	-41.104	-11.422	4.620

Panel B.

Variables	LH N_1	SH N_2	LH μ_1	SH μ_2	LH-SH Diff	t-stat
Fund characteristics						
Assets	114,221	114,046	2.376	0.936	1.440***	(6.336)
Age	114,221	114,044	16.178	13.615	2.562***	(6.556)
Turn_ratio	112,796	112,938	68.907	70.811	−1.904***	(-5.927)
Expense ratio	108,978	111,975	1.050	1.171	−0.121***	(-9.610)
Load	114,221	114,046	0.555	0.356	0.199***	(12.042)
H-Horizon	105,665	104,597	3.017	2.809	0.208***	(4.721)
Clientele						
DC ratio	29,237	13,033	0.222	0.186	0.036***	(3.294)
Monthly returns (Forward)						
Total returns	114,221	114,046	0.828	0.754	0.074***	(4.461)
Net returns	114,221	114,046	0.748	0.663	0.085***	(5.082)
Benchmark adj. returns	89,247	86,597	-0.093	-0.169	0.076***	(7.838)
CS	98,711	92,777	-0.001	-0.023	0.022***	(3.427)
4F alpha	112,020	111,152	-0.054	-0.105	0.051***	(5.521)
Buy-Hold returns						
$BHAR_{net,12}$	88,894	86,176	-0.290	-1.157	0.867***	(7.752)
$BHAR_{net,36}$	88,787	86,036	-5.620	-9.175	3.555***	(7.086)
$BHAR_{net,60}$	87,463	84,598	-18.422	-24.600	6.178***	(5.652)

Table 3: Manager Evaluation Horizon and Portfolio Holding Horizon. This table shows the results of OLS regressions where the dependent variable is fund portfolio turnover in Columns (1) and (2) and portfolio-implied horizon as calculated in Lan et al. (2024) in Columns (3) and (4). Portfolio-implied horizons are adjusted by fund style using CRSP objective codes. All variables are described in Table B.1 in the Appendix. Standard errors are double clustered at the fund and month levels. *t*-statistics are reported in parentheses and significance levels are denoted by *, **, ***, which correspond to 10%, 5%, and 1% levels, respectively.

	(1) Turnover	(2) Turnover	(3) Portfolio implied horizon	(4) Portfolio implied horizon
LH (t-1)	-0.035**	-0.036**	0.283***	0.075**
	(-2.290)	(-2.302)	(6.739)	(2.096)
lnAssets (t-1)		-0.037***		0.242***
		(-6.195)		(15.623)
Exp ratio (t-1)		-0.012		0.143**
		(-0.354)		(2.137)
Flow (t-1, t)		-0.130***		-1.320***
		(-4.029)		(-6.767)
I(load)		-0.008		-0.121***
		(-0.505)		(-3.186)
Turn ratio (t-1)				-0.288***
				(-9.381)
Constant	0.717***	0.683***	-0.157***	0.356***
	(90.59)	(17.84)	(-5.423)	(4.929)
N	195,883	188,792	208,623	198,802
Adj. R^2	0.886	0.881	0.461	0.555
Time FE	Y	Y	Y	Y
Style FE	Y	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time	Fund-Time

Table 4: Fire Sale Stocks and Evaluation Horizons. Panel A reports results for the following OLS regression model:

$$\Delta shares(q+k)_{i,s,q} = \alpha + \beta_1 LH_{i,q} + \beta_2 X_{s,q} + \beta_3 X_{i,q} + \beta_4 X_q + \epsilon_{i,s,q},$$

where q is the quarter when stock s becomes a 'fire-sale' stock and the dependent variable is the change in the number of shares held by fund i in fire-sale stock s over two adjacent quarters, scaled by the stock's total number of shares outstanding. k ranges from -2 to $+3$. LH is an indicator that takes the value of one if fund i is a long-horizon fund and zero otherwise. $X_{s,q}$ captures stock characteristics such as illiquidity (ILLIQ), return momentum, size, idiosyncratic volatility over the past two years (VOL), and book-to-market ratio (BM); and $X_{i,q}$ captures fund size. Fire sale stocks are identified using the implied price pressure measure in Edmans et al. (2012). Each quarter, fire-sales stocks are those in the bottom 10 percentiles of this measure. We standardize the dependent variable using the standard deviation of all trades of funds. Panel B includes interaction terms between the LH dummy and various stock characteristics. Results are reported for the quarter following the fire-sale event. Panel C includes an interaction term between LH and the fund's flow-performance sensitivity in Column (1). In Columns (2) and (3), distressed funds are excluded from the sample. Standard errors are double clustered at the fund and quarter levels. t-statistics are reported in parentheses and significance levels are denoted by *, **, ***, which correspond to 10%, 5%, and 1% levels, respectively.

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)
k	-2	-1	0	$+1$	$+2$	$+3$
LH	-0.024	-0.002	0.022	0.034**	0.038**	0.017
	(-0.633)	(-0.048)	(1.111)	(2.015)	(2.028)	(0.778)
ILLIQ	0.060	0.040**	-0.007	-0.006	0.089	0.211
	(0.844)	(2.497)	(-0.610)	(-1.012)	(0.776)	(1.056)
Momentum	0.001	-0.059	-0.011	-0.024	0.017	0.008
	(0.021)	(-1.083)	(-0.256)	(-1.222)	(0.688)	(0.358)
Size	-0.107***	-0.060***	-0.030***	-0.021***	-0.028***	-0.017*
	(-3.715)	(-5.953)	(-3.978)	(-3.346)	(-4.616)	(-1.778)
Vol	0.044***	0.045***	0.032***	0.021**	0.022*	0.025**
	(3.019)	(3.084)	(3.300)	(2.660)	(1.874)	(2.416)
BM	-0.007	-0.024	0.047	-0.047**	-0.026	0.066
	(-0.370)	(-1.187)	-0.767	(-2.292)	(-0.757)	(0.670)
logTNA	0.128***	0.081***	0.039***	0.009	0.012*	0.016**
	(4.936)	(5.161)	(5.634)	(1.429)	(1.937)	(2.153)
N	108,801	114,965	115,231	105,643	102,689	98,135
Adj. R^2	0.045	0.036	0.007	0.003	0.004	0.005
Time FE	Y	Y	Y	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time

Panel B. Stock characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
k	+1	+1	+1	+1	+1	+1
LH	0.349**	-0.005	0.034**	0.008	0.033*	0.243*
	(2.623)	(-0.259)	(2.022)	(0.352)	(1.916)	(1.680)
LH x Size	-0.021**					-0.017*
	(-2.634)					(-1.996)
LH x Vol		0.027**				0.015
		(2.205)				(1.263)
LH x ILLIQ			-0.001			-0.021
			(-0.023)			(-0.873)
LH x BM				0.047		0.027
				(1.325)		(0.679)
LH x MOM					0.009	0.031
					(0.240)	(0.783)
ILLIQ	-0.006	-0.006	-0.006**	-0.005	-0.006	-0.000
	(-0.876)	(-0.920)	(-2.033)	(-0.798)	(-1.013)	(-0.094)
Momentum	-0.024	-0.024	-0.024	-0.024	-0.03	-0.041*
	(-1.206)	(-1.200)	(-1.223)	(-1.191)	(-1.334)	(-2.011)
Size	-0.009	-0.021***	-0.021***	-0.021***	-0.021***	-0.012
	(-1.242)	(-3.344)	(-3.344)	(-3.348)	(-3.344)	(-1.519)
Vol	0.021**	0.005	0.021**	0.021**	0.021**	0.012
	(2.657)	(0.422)	(2.658)	(2.677)	(2.655)	(1.113)
BM	-0.046**	-0.047**	-0.047**	-0.073**	-0.047**	-0.061
	(-2.255)	(-2.274)	(-2.294)	(-2.078)	(-2.293)	(-1.625)
logTNA	0.009	0.009	0.009	0.009	0.009	0.009
	(1.472)	(1.424)	(1.429)	(1.435)	(1.430)	(1.467)
N	105,643	105,643	105,643	105,643	105,643	105,643
Adj. R^2	0.003	0.003	0.003	0.003	0.003	0.003
Time FE	Y	Y	Y	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time

Panel C. Fund characteristics

	(1)	(2)	(3)
k	+1	+1	+1
		Exclude if fund flows < P10	
		Nondistressed funds	Nondistressed funds
LH	0.058**	0.030**	0.049*
	(2.320)	(2.175)	(1.909)
LH x FPS	-0.036*		-0.036*
	(-1.840)		(-1.858)
ILLIQ	0.021	-0.009	0.010
	(0.570)	(-1.483)	(0.274)
Momentum	0.038	-0.033	0.041
	(0.848)	(-1.457)	(0.885)
Size	-0.039***	-0.027***	-0.044***
	(-3.628)	(-4.860)	(-4.305)
Vol	0.029*	0.023***	0.031*
	(1.846)	(3.020)	(1.869)
BM	-0.094**	-0.048**	-0.083*
	(-2.393)	(-2.201)	(-1.969)
logTNA	0.018*	0.017***	0.024**
	(1.798)	(2.919)	(2.325)
N	34,366	93,574	32,564
Adj. R^2	0.006	0.003	0.006
Time FE	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time

Table 5: Cumulative Loadings on Dividend Strips. This table shows the cumulative loadings of fund returns on long- and short-horizon risks. We follow the methodology of Gonçalves (2021) to construct horizon-specific risk factors. For each fund, we find the risk loadings for the risk factors, which are then aggregated by the fund's evaluation horizons. Significance levels are denoted by *, **, ***, which correspond to 10%, 5%, and 1% levels, respectively.

Risk horizon h	LH	SH	LH−SH	t-stat
[1, 5]	0.2240	0.2747	-0.0507***	-3.02
[6, 20]	0.2659	0.2542	0.0117**	2.10
[6, 30]	0.4365	0.4113	0.0253***	2.84
[6, 40]	0.6063	0.5682	0.0381***	3.00
[6, 50]	0.7760	0.7253	0.0507***	3.02

Table 6: Fund Performance and Evaluation Horizon. This table shows the results of OLS regressions where the dependent variable is the performance of long- and short-horizon funds. The unit of analysis is fund × month. We measure fund performance (in percentages) in Columns (1) as the monthly net return, in Column (2) as the monthly net return in excess of the benchmark return, in Column (3) as the four factor alpha using net returns, and in Column (4) as the DGTW return. Columns (5), (6), and (7) show the buy and hold returns of the fund minus that of the buy-and-hold return of the benchmark over the following year ("BHAR 1 year"), the following three years ("BHAR 3 year"), and the following five years ("BHAR 5 year"). The explanatory variables are the same as those in Table 3 and are described in Table B.1 in the Appendix. Standard errors are clustered at the fund and month levels. t-statistics are reported in parentheses and significance levels are denoted by *, **, ***, which correspond to 10%, 5%, and 1% levels, respectively.

	(1) Net rets	(2) Benchmark adjusted net rets	(3) 4F alpha	(4) DGTW	(5) BHAR 1 year	(6) BHAR 3 year	(7) BHAR 5 year
LH (t-1)	0.054***	0.047***	0.028***	0.017**	0.663***	2.303***	4.101***
	(4.355)	(4.675)	(2.923)	(2.571)	(5.459)	(4.907)	(4.545)
lnAssets (t-1)	0.013**	0.006**	0.003	0.005**	0.187***	1.426***	3.022***
	(2.195)	(2.027)	(0.915)	(2.323)	(4.535)	(9.136)	(10.069)
Turn ratio (t-1)	-0.059***	-0.053***	-0.040***	-0.004	-0.702***	-1.974***	-3.088***
	(-4.726)	(-4.121)	(-3.367)	(-0.616)	(-5.095)	(-5.311)	(-5.535)
Exp ratio (t-1)	-0.092***	-0.105***	-0.079***	0.012	-0.195	0.136	0.139
	(-3.790)	(-6.361)	(-3.949)	(0.849)	(-0.882)	(0.158)	(0.087)
Flow (t-1,t)	-0.050	0.056	0.300***	-0.010	2.439**	18.834***	44.600***
	(-0.375)	(0.590)	(2.949)	(-0.172)	(2.483)	(6.024)	(8.163)
I(load)	-0.008	0.003	-0.002	-0.004	-0.020	-0.625	-1.137
	(-0.585)	(0.270)	(-0.173)	(-0.593)	(-0.158)	(-1.255)	(-1.207)
Constant	0.828***	0.02	0.027	-0.022	-0.068	-5.204***	-17.359***
	(30.950)	(1.100)	(1.295)	(-1.550)	(-0.291)	(-5.759)	(-10.427)
N	217,577	167,510	213,053	186,085	166,570	166,323	163,776
Adj. R^2	0.708	0.053	0.054	0.12	0.17	0.284	0.473
Time FE	Y	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time

Table 7: Portfolio Characteristics, Fund Performance, and Evaluation Horizon around Across-Family Fund Mergers. This table reports the results of difference-in-difference analyses where the dependent variables are fund portfolio characteristics (Columns (1)–(2)) and performance (Columns (3)–(9)) around family mergers. We follow the methodology of McLemore (2019) to identify merger events. The treatment group consists of funds that change their evaluation horizon from short horizon to long horizon after the merger. The control group consists of funds that keep the same horizon. Treated and control funds are matched based on assets, turn ratio, expense ratio, and flow, prior to their family merger. The table below uses 1-to-3 matching between the treatment and control groups. $After$ takes the value of one after the merger and zero otherwise. The control variables are identical to those in Table 3. Standard errors are double clustered at the fund and month levels. t-statistics are reported in parentheses and significance levels are denoted by *, **, ***, which correspond to 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Turnover	Portfolio implied horizon	Net rets.	Benchmark adjusted net rets.	4F alpha	DGTW	BHAR 1 year	BHAR 2y 2 year	BHAR 3 year
DiD	-0.022	0.108*	0.046	0.126**	0.063**	0.064***	0.768**	1.121***	1.780***
	(-0.442)	(1.746)	(1.221)	(2.147)	(2.509)	(2.731)	(2.584)	(2.933)	(3.900)
Treat	-0.162***	0.216**	-0.012	-0.010	0.035**	-0.003	-0.051	0.113	0.565
	(-4.190)	(1.976)	(-0.627)	(-0.219)	(2.288)	(-0.166)	(-0.224)	(0.475)	(1.628)
After	0.029	0.044	-0.096***	-0.109***	-0.058**	-0.024	-1.140***	-0.909***	-0.491*
	(0.916)	(0.754)	(-3.793)	(-3.058)	(-2.509)	(-1.500)	(-5.512)	(-3.631)	(-1.810)
lnAssets (t-1)	-0.058***	0.065**	0.006	-0.008**	-0.008	-0.010***	-0.007	0.094	0.293***
	(-5.841)	(1.985)	(0.575)	(-2.415)	(-1.293)	(-3.874)	(-0.166)	(1.429)	(5.392)
Turn ratio (t-1)		-0.378***	-0.084***	-0.024	-0.025	-0.041**	-0.293	-0.888***	-1.224***
		(-4.084)	(-3.206)	(-0.973)	(-1.600)	(-2.456)	(-1.580)	(-3.708)	(-3.703)
Exp ratio (t-1)	0.121***	0.132	-0.079**	-0.023	-0.034	-0.033**	-0.274	-0.394	0.033
	(2.676)	(0.768)	(-2.357)	(-1.096)	(-1.006)	(-2.569)	(-1.390)	(-1.183)	(0.082)
Flow (t-1,t)	-1.145***	-1.046*	-0.869***	-0.378	0.426*	-0.032	-1.001	-6.834***	-4.125
	(-6.042)	(-1.905)	(-3.034)	(-1.441)	-1.705	(-0.206)	(-0.532)	(-2.707)	(-1.423)
I (load)	0.052*	-0.104	-0.043**	0.060***	0.004	0.021**	-0.054	-0.425	-0.957***
	(1.713)	(-0.950)	(-2.352)	(4.038)	(0.160)	(2.216)	(-0.281)	(-1.483)	(-2.806)
Constant	0.571***	-0.552***	0.337***	-0.002	0.082**	0.059***	0.968***	-0.938**	-5.843***
	(10.545)	(-2.733)	(6.673)	(-0.074)	(2.372)	(2.912)	(3.377)	(-2.154)	(-11.609)
N	45,432	45,431	45,431	39,842	42,504	41,477	40,673	40,673	40,665
Adj. R^2	0.129	0.606	0.817	0.067	0.08	0.229	0.272	0.551	0.601
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time

Table 8: Manager Turnover and Evaluation Horizon. This table reports results for OLS regressions that test the sensitivity of manager turnover to performance across short- and long-horizon funds. The dependent variable takes the value of one in Columns (1)-(3) if the manager is promoted and zero otherwise. The corresponding demotion results are reported in Columns (4)-(6). We identify manager promotions or demotions using multiple criteria - size of the old vs. new funds they manage, lead manager status before and after the turnover, and the change in the number of funds managed. We then average promotions or demotions across the manager team at the fund level. The explanatory variables of interest are the interactions between the LH indicator and fund performance. Fund performance is measured by holding period return (HPR) over the past 1, 2, and 3 years, respectively. Each year we divide the sample into two groups using the binary variables 'High cum HPR' and 'Low cum HPR'. For instance, 'High cum HPR (t-1,t)' takes the value of one if the fund's cumulative HPR in the past 1 year is above the median or 0 otherwise. The control variables are the same as those in Table 3. The unit of analysis is fund $\times$ year. Standard errors are clustered by fund and year. t-statistics are reported in parentheses and significance levels are denoted by *, **, ***, which correspond to 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
LH (t-1) × High cum HPR (t-1,t)	0.0163***					
	(2.9304)					
High cum HPR (t-1,t)	-0.0035					
	(-1.4491)					
LH (t-1) × High cum HPR (t-2,t)		0.0097*				
		(1.8944)				
High cum HPR (t-2,t)		-0.0007				
		(-0.1870)				
LH (t-1) × High cum HPR (t-3,t)			0.0114**			
			(2.2920)			
High cum HPR (t-3,t)			-0.0009			
			(-0.2401)			
LH (t-1) × Low cum HPR (t-1,t)				0.0016		
				(1.2540)		
Low cum HPR (t-1,t)				-0.0002		
				(-1.2578)		
LH (t-1) × Low cum HPR (t-2,t)					0.0008	
					(0.9558)	
Low cum HPR (t-2,t)					-0.0001	
					(-0.9792)	
LH (t-1) × Low cum HPR (t-3,t)						0.0015**
						(2.0177)
Low cum HPR (t-3,t)						-0.0001
						(-0.7886)
LH (t-1)	0.0486***	0.0519***	0.0509***	0.0013	0.0017*	0.0014*
	(5.9918)	(6.0839)	(5.8210)	(1.6004)	(1.8898)	(1.8272)
lnAssets (t)	0.0011	0.0011	0.0011	0.0001	0.0001	0.0001
	(0.9246)	(0.9081)	(0.8937)	(0.7040)	(0.6581)	(0.7199)
Turn ratio (t)	-0.0006	-0.0006	-0.0006	0.0003**	0.0003**	0.0003**
	(-0.3360)	(-0.3524)	(-0.3509)	(2.0538)	(2.1101)	(2.1219)
Exp ratio (t)	-0.0021	-0.0021	-0.002	-0.0002	-0.0002	-0.0002
	(-0.3532)	(-0.3474)	(-0.3377)	(-0.2570)	(-0.2513)	(-0.2750)
Flow (t)	-0.0232	-0.0258	-0.0283	-0.013	-0.0134	-0.0124
	(-0.2561)	(-0.2847)	(-0.3171)	(-0.8903)	(-0.8464)	(-0.8193)
I (load) (t)	0.0036	0.0035	0.0035	0.0006	0.0006	0.0006
	(0.9011)	(0.8838)	(0.8709)	(1.2902)	(1.3073)	(1.3063)
Constant	0.0219**	0.0202*	0.0201*	0.0009	0.0009	0.001
	(2.0327)	(1.8245)	(1.8095)	(0.6141)	(0.5847)	(0.6373)
N	17,809	17,809	17,809	17,808	17,808	17,808
Adj. R^2	0.0359	0.0356	0.0357	-0.0031	-0.0033	-0.0031
Year FE	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time

Table 9: Fund Characteristics and Evaluation Horizons. The table reports results for OLS regressions where the dependent variable is the binary variable LH that takes the value of one for long-horizon funds, and 0 otherwise. The unit of analysis is fund $\times$ year. Our main explanatory variables of interest are measures of investor patience in Columns (1) and (2), the availability of lending facilities in Columns (3) and (4), and manager tenure in columns (5) and (6). All variables in the table are described in Table B.1 in the Appendix. Panel A shows the results without additional controls, while Panel B adds our baseline control variables from Table 3. Standard errors are clustered by fund and year. t-statistics are reported in parentheses and significance levels are denoted by *, **, ***, which correspond to 10%, 5%, and 1% levels, respectively.

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES				2018 only		
FPS	-0.0002**					
	(-2.5145)					
DC ratio		0.2812**				
		(2.6736)				
Has_MMF			0.3047***			
			(12.0626)			
ILP_LC				0.2783***		
				(4.6402)		
Avg Mgr tenure					-0.0059***	
					(-3.0296)	
Lead Mgr Tenure						-0.002
						(-1.2299)
Constant	0.4966***	0.6305***	0.3875***	0.2741***	0.5320***	0.5193***
	(59.4439)	(22.1067)	(32.0242)	(6.5246)	(37.7223)	(25.5731)
N	19,796	3,655	19,796	908	19,796	19,796
Adj. R^2	0.003	0.0272	0.0857	0.0782	0.0048	0.0032
Time FE	Y	Y	Y	N	Y	Y
Style FE	Y	Y	Y	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time	Family	Fund-Time	Fund-Time

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES				2018 only		
FPS	-0.0001**					
	(-2.3214)					
DC ratio		0.1974*				
		(1.9232)				
Has_MMF			0.1949***			
			(9.3373)			
ILP_LC				0.1853***		
				(3.2456)		
Avg Mgr tenure					-0.0084***	
					(-4.2649)	
Lead Mgr Tenure						-0.0042**
						(-2.8196)
lnAssets (t-1)	0.0573***	0.0389***	0.0454***	0.0575***	0.0602***	0.0587***
	(9.8343)	(3.3398)	(8.4653)	(5.2664)	(10.8239)	(10.3106)
Turn ratio (t-1)	0.0148	0.0623**	0.0078	0.0015	0.0112	0.0128
	(1.6208)	(2.2401)	(0.8690)	(0.0782)	(1.2530)	(1.4310)
Exp ratio (t-1)	-0.1480***	-0.0898	-0.1096***	-0.1414**	-0.1384***	-0.1444***
	(-6.2491)	(-1.2363)	(-5.1663)	(-2.2551)	(-5.6133)	(-6.0155)
Flow (t,t-1)	0.1151	-0.1885	0.0424	0.2450	0.0984	0.1090
	(1.3691)	(-0.7918)	(0.5140)	(0.7527)	(1.1656)	(1.2962)
I (load)	0.2085***	0.1359***	0.1644***	0.2010***	0.2040***	0.2065***
	(10.3049)	(3.1462)	(8.6039)	(3.3248)	(9.9573)	(10.0535)
Constant	0.6159***	0.5974***	0.5128***	0.4571***	0.6639***	0.6643***
	(25.0420)	(6.8817)	(21.6106)	(6.0548)	(24.7565)	(21.9275)
N	18,862	3,620	18,862	859	18,862	18,862
Adj. R^2	0.1281	0.0703	0.1563	0.2072	0.1318	0.1296
Time FE	Y	Y	Y	N	Y	Y
Style FE	Y	Y	Y	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time	Family	Fund-Time	Fund-Time

APPENDIX

Contract Evaluation Horizon and Fund Performance

July 28, 2025

EXHIBIT 1: Examples of Long Horizon Evaluations

Example 1: Wellington 2012

Compensation: Wellington Management receives a fee based on the assets under management of each Fund as set forth in the Investment Subadvisory Agreement between Wellington Management and the Manager on behalf of each Fund. Wellington Management pays its investment professionals out of its total revenues, including the advisory fees earned with respect to each Fund. The following information relates to the fiscal year ended July 31, 2016.

Wellington Management's compensation structure is designed to attract and retain high-caliber investment professionals necessary to deliver high quality investment management services to its clients. Wellington Management's compensation of each Fund's managers listed in the prospectuses who are primarily responsible for the day-to-day management of the Funds (the 'Investment Professionals') includes a base salary and incentive components. The base salary for each Investment Professional who is a partner (a 'Partner') of Wellington Management Group LLP, the ultimate holding company of Wellington Management, is generally a fixed amount determined by the managing partners of Wellington Management Group LLP. *Each Investment Professional is eligible to receive an incentive payment based on the revenues earned by Wellington Management from the Fund managed by the Investment Professional and generally each other account managed by such Investment Professional. Each Investment Professional's incentive payment relating to the relevant Fund is linked to the gross pre-tax performance of the portion of the Fund managed by the Investment Professional compared to the benchmark index and/or peer group identified below over one and three year periods, with an emphasis on three year results. In 2012, Wellington Management began placing increased emphasis on long-term performance and is phasing in a five-year performance comparison period, which will be fully implemented by December 31, 2016.* Wellington Management applies similar incentive compensation structures (although the benchmarks or peer groups, time periods and rates may differ) to other accounts managed by the Investment Professionals, including accounts with performance fees.

Portfolio-based incentives across all accounts managed by an investment professional can, and typically do, represent a significant portion of an investment professional's overall compensation; incentive compensation varies significantly by individual and can vary significantly from year to year. The Investment Professionals also may be eligible for bonus payments based on their overall contribution to Wellington Management's business operations. Senior management at Wellington Management may reward individuals as it deems appropriate based on other factors. Each Partner is eligible to participate in a Partner-funded tax qualified retirement plan, the contributions to which are made pursuant to an actuarial formula.

Example 2: Pioneer 2012

Pioneer has adopted a system of compensation for portfolio managers that seeks to align the financial interests of the portfolio managers with those of shareholders of the accounts (including Pioneer funds) the portfolio managers manage, as well as with the financial performance of Pioneer. The compensation program for all Pioneer portfolio managers includes a base salary (determined by the rank and tenure of the employee) and an annual bonus program, as well as customary benefits that are offered generally to all full-time employees. Base compensation is fixed and normally reevaluated on an annual basis. Pioneer seeks to set base compensation at market rates, taking into account the experience and responsibilities of the portfolio manager. The bonus plan is intended to provide a competitive level of annual bonus compensation that is tied to the portfolio manager achieving superior investment performance and align the interests of the investment professional with those of shareholders, as well as with the financial performance of Pioneer. Any bonus under the plan is completely discretionary, with a maximum annual bonus that may be in excess of base salary. The annual bonus is based upon a combination of the following factors:

o QUANTITATIVE INVESTMENT PERFORMANCE. *The quantitative investment performance calculation is based on pre-tax investment performance of all of the accounts managed by the portfolio manager (which includes the fund and any other accounts managed by the portfolio manager) over a one-year period (20% weighting) and four-year period (80% weighting), measured for periods ending on December 31.* The accounts, which include the fund, are ranked against a group of mutual funds with similar investment objectives and investment focus (60%) and a broad-based securities market index measuring the performance of the same type of securities in which the accounts invest (40%), which, in the case of the fund, is the Russell 1000 Growth Index. As a result of these two benchmarks, the performance of the portfolio manager for compensation purposes is measured against the criteria that are relevant to the portfolio manager's competitive universe.

o QUALITATIVE PERFORMANCE. The qualitative performance component with respect to all of the accounts managed by the portfolio manager includes objectives, such as effectiveness in the areas of teamwork, leadership, communications and marketing, that are mutually established and evaluated by each portfolio manager and management.

Example 3: T.Rowe Price 2017

Portfolio manager compensation consists primarily of a base salary, a cash bonus, and an equity incentive that usually comes in the form of restricted stock grant. Compensation is variable and is determined based on the following factors. Investment performance over 1-, 3-, 5-, and 10-year periods is the most important input. The weightings for these time periods are generally balanced and are applied consistently across similar strategies. T. Rowe Price (and Price Hong Kong, Price Singapore, and T. Rowe Price International, as appropriate), evaluate performance in absolute, relative, and risk-adjusted terms. Relative performance and risk-adjusted performance are typically determined with reference to the broad-based index (e.g., S&P 500 Index) and the Lipper index (e.g., Large-Cap Growth) set forth in the total returns table in the fund's prospectus, although other benchmarks may be used as well. Investment results are also measured against comparably managed funds of competitive investment management firms. The selection of comparable funds is approved by the applicable investment steering committee (as described under the "Disclosure of Fund Portfolio Information" section) and is the same as the selection presented to the directors of the Price Funds in their regular review of fund performance. *Performance is primarily measured on a pretax basis though tax efficiency is considered and is especially important for the Tax-Efficient Equity Fund.*

Compensation is viewed with a long-term time horizon. The more consistent a manager's performance over time, the higher the compensation opportunity. The increase or decrease in a fund's assets due to the purchase or sale of fund shares is not considered a material factor. In reviewing relative performance for fixed-income funds, a fund's expense ratio is usually taken into account. Contribution to T. Rowe Price's overall investment process is an important consideration as well. Leveraging ideas and investment insights across the global investment platform, working effectively with and mentoring others, and other contributions to our clients, the firm or our culture are important components of T. Rowe Price's long-term success and are highly valued.

All employees of T. Rowe Price, including portfolio managers, participate in a 401(k) plan sponsored by T. Rowe Price Group. In addition, all employees are eligible to purchase T. Rowe Price common stock through an employee stock purchase plan that features a limited corporate matching contribution. Eligibility for and participation in these plans is on the same basis for all employees. Finally, all vice presidents of T. Rowe Price Group, including all portfolio managers, receive supplemental medical/hospital reimbursement benefits.

This compensation structure is used when evaluating the performance of all portfolios (including the Price Funds) managed by the portfolio manager.

Table A.1: Robustness Test 1. Fire sale stocks using the DL measure and Evaluation Horizon. Panel A reports the changes of shares of fire sale stocks held by funds between two consecutive quarters relative to shares outstanding at the end of the prior quarter. Fire sale stocks are defined by using the methodology of Lou (2012). The variable k refers to the quarter relative to the fire sale quarter, varying from -2 to $+3$. Standard errors are clustered by fund and by time. The description of the variables is included in Table B.1 in the Appendix.

	(1)	(2)	(3)	(4)	(5)	(6)
k	-2	-1	0	$+1$	$+2$	$+3$
LH	-0.020	0.025	0.028	0.075***	0.026	0.044*
	(-0.488)	-0.751	-1.351	-3.479	-1.37	-1.991
ILLIQ	0.006	0.013	-0.059	0.256	-0.010	-0.014
	-0.128	-0.267	(-1.433)	-0.886	(-0.642)	(-0.502)
Momentum	0.024	-0.022	0.015	0.031	0.007	0.062***
	(0.640)	(-0.445)	(0.420)	(1.483)	(0.390)	(3.140)
Size	-0.111***	-0.095***	-0.044***	-0.035***	-0.043***	-0.037***
	(-8.061)	(-6.951)	(-3.764)	(-3.284)	(-4.389)	(-3.228)
Vol	0.050	0.043*	0.023	0.048*	-0.000	0.030
	(1.445)	(1.706)	(1.223)	(1.754)	(-0.037)	(1.607)
BM	0.029	-0.043**	-0.023	0.017	-0.055**	-0.022
	(0.746)	(-2.099)	(-1.018)	-0.422	(-2.410)	(-1.102)
logTNA	0.119***	0.085***	0.060***	0.050***	0.041***	0.035***
	(8.453)	(6.413)	(5.802)	(6.114)	(4.615)	(4.130)
Observations	47,889	49,208	48,199	46,396	44,471	43,277
R-squared	0.025	0.026	0.009	0.009	0.008	0.006
Time FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y

Table A.2: Fund Performance, Evaluation Horizon, and Fund Holding Horizon In this table, we reproduce Table 6 by including an addition explanatory variable, 'H-H', which is a measure of the fund's holding horizon as developed by Lan, Moneta, and Wermers (2024). The dependent variables are (1) the monthly net returns, (2) the monthly net returns in excess of the benchmark returns, (3) the four factor alpha using net returns, (4) the monthly gross returns, (5) the monthly gross returns in excess of the benchmark returns, (6) the four factor alpha before expense, (7) DGTW return. Standard errors are clustered by fund and by time.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Net Raw returns	Net Benchmark Adj.	Net 4 factor alpha	Gross Raw returns	Gross Benchmark Adj.	Gross 4 factor alpha	Stock-based DGTW
Long horizon (t-1)	0.075***	0.075***	0.030*	0.076***	0.076***	0.030*	0.064***
	(2.745)	(3.759)	(1.795)	(2.789)	(3.837)	(1.795)	(3.934)
H-H measure (t-1)	0.039**	0.023**	0.004	0.040**	0.023**	0.004	0.012
	(2.427)	(2.574)	(0.510)	(2.437)	(2.599)	(0.510)	(1.253)
lnAssetsB (t-1)	−0.198***	−0.147***	−0.011	−0.198***	−0.147***	−0.011	−0.099***
	(-9.134)	(-10.881)	(-1.568)	(-9.097)	(-10.872)	(-1.568)	(-8.320)
lnAge (t-1)	−0.009	−0.015	0.026	−0.011	−0.015	0.026	0.018
	(-0.236)	(-0.586)	-1.244	(-0.282)	(-0.618)	-1.244	-0.845
Turn ratio (t-1)	0.012	−0.029*	−0.037***	0.011	−0.030*	−0.037***	0.021
	(0.553)	(-1.821)	(-2.643)	(0.510)	(-1.903)	(-2.643)	(1.442)
Exp ratio (t-1)	0.004	0.039	−0.020	0.066	0.079*	−0.020	0.088*
	(0.062)	(0.775)	(-0.719)	(0.974)	(1.665)	(-0.719)	(1.734)
Flow (t-1, t)	−0.072	−0.086*	0.176***	−0.074	−0.088*	0.176***	−0.055
	(-0.848)	(-1.908)	(2.798)	(-0.864)	(-1.932)	(2.798)	(-0.991)
Constant	0.268*	−0.313***	−0.094	0.295**	−0.266***	−0.094	−0.330***
	(1.934)	(-3.358)	(-1.479)	(2.121)	(-2.897)	(-1.479)	(-3.428)
Observations	99,548	88,860	66,500	99,550	88,862	66,500	100,803
Adjusted R2	0.842	0.211	0.019	0.842	0.209	0.019	0.265
Year-Month FE	Y	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y
Cluster SE	Fund and Time	Fund and Time	Fund and Time	Fund and Time	Fund and Time	Fund and Time	Fund and Time

Table A.3: Fund Performance and Evaluation Horizon - Matched Sample In this table, we re-estimate Table 6 for a matched sample. The matching approach minimizes the Gaussian distance of fund characteristics, which include fund style, size, age, expense ratio, turnover ratio, flow, and performance in the prior month. Fund styles are based on 2-digit CRSP objective codes. The dependent variables are (1) the monthly net returns, (2) the monthly net returns in excess of the benchmark returns, (3) the four factor alpha using net returns, (4) the monthly gross returns, (5) the monthly gross returns in excess of the benchmark returns, (6) the four factor alpha before expense, (7) DGTW return. Standard errors are clustered by fund and by time.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Long horizon (t-1)	0.057***	0.031*	0.053***	0.058***	0.031*	0.053***	0.031**
	(2.723)	(1.769)	(2.802)	(2.728)	(1.767)	(2.806)	(2.524)
lnAssetsB (t-1)	−0.011	−0.019***	−0.014**	−0.011	−0.018***	−0.014**	−0.006
	(-1.284)	(-2.628)	(-1.986)	(-1.278)	(-2.615)	(-1.981)	(-1.215)
lnAge (t-1)	0.058***	0.055***	0.078***	0.058***	0.055***	0.078***	0.042***
	(2.785)	(3.509)	(3.772)	(2.793)	(3.509)	(3.767)	(3.507)
Turn ratio (t-1)	−0.063**	−0.069**	−0.043*	−0.062**	−0.069**	−0.043*	−0.049***
	(-2.310)	(-2.577)	(-1.724)	(-2.307)	(-2.569)	(-1.725)	(-2.826)
Exp ratio (t-1)	1.793	−8.543**	−7.871**	9.675*	−0.727	−0.005	−0.008
	(0.324)	(-2.134)	(-2.152)	(1.747)	(-0.181)	(-0.001)	(-0.003)
Flow (t-1, t)	−0.007***	−0.004***	−0.002*	−0.007***	−0.004***	−0.002**	−0.001
	(-3.297)	(-3.547)	(-1.898)	(-3.337)	(-3.654)	(-2.086)	(-0.592)
Constant	0.398***	−0.099*	−0.201***	0.402***	−0.094*	−0.197***	−0.115***
	(5.318)	(-1.811)	(-2.969)	(5.364)	(-1.722)	(-2.903)	(-2.666)
N of Obs	47,275	41,239	32,170	47,275	41,239	32,170	47,268
Adj. R^2	0.882	0.072	0.053	0.882	0.073	0.052	0.229
Time FE	Y	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y	Y

Table A.4: Lead manager fixed effect This table shows the effect of evaluation horizon on Portfolio characteristics by taking into account the lead manager fixed effect. Panel A shows the multivariate analysis for portfolio characteristics. Portfolio implied horizons in Columns (2) and (3) are adjusted for fund style. Panel B shows the multivariate analysis for fund performance. Standard errors are clustered by fund and time. A detailed description of the variables is provided in Table B.1 in the Appendix.

Panel A.

	(1)	(2)	(3)
	Turnover	Portfolio implied measure	Portfolio implied measure
LH (t-1)	-0.017**	0.291***	0.083*
	(-2.276)	(5.797)	(1.950)
lnAssets (t-1)	-0.014***		0.270***
	(-4.936)		(15.187)
Turn ratio (t-1)	0.551***		-0.264***
	(29.289)		(-6.689)
Expense ratio (t-1)	-0.005		0.208***
	(-0.239)		(2.763)
Flow (t-1,t)	-0.019		-1.101***
	(-0.904)		(-6.353)
I(load)	-0.002		-0.110**
	(-0.216)		(-2.406)
Constant	0.303***	-0.106***	0.348***
	(10.415)	(-3.494)	(4.168)
Observations	215,921	208,595	198,775
Adjusted R^2	0.947	0.577	0.647
Year-Month FE	Y	Y	Y
Style FE	Y	Y	Y
Lead manager FE	Y	Y	Y

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Net ret	Benchmark adjusted net ret	4F alpha	DGTW	BHAR 1 year	BHAR 3 years	BHAR 5 years
LH (t-1)	0.065***	0.051***	0.045***	0.025***	0.888***	3.163***	5.199***
	(4.322)	(3.763)	(3.713)	(3.050)	(5.813)	(5.408)	(5.126)
lnAssets (t-1)	0.007	-0.002	-0.005	0.002	0.122**	1.538***	3.015***
	(1.068)	(-0.447)	(-1.254)	(0.869)	(2.540)	(8.127)	(9.313)
Turn ratio (t-1)	-0.080***	-0.063***	-0.056***	-0.002	-0.821***	-2.009***	-3.083***
	(-5.846)	(-4.284)	(-4.244)	(-0.359)	(-5.051)	(-4.247)	(-4.619)
Exp. ratio (t-1)	-0.090***	-0.101***	-0.102***	0.028*	-0.127	0.652	0.943
	(-3.175)	(-4.555)	(-4.594)	(1.780)	(-0.501)	(0.589)	(0.494)
Flow (t-1,t)	-0.307**	-0.244***	0.083	-0.152***	-1.438	8.824***	23.600***
	(-2.428)	(-2.618)	(0.828)	(-2.621)	(-1.412)	(2.970)	(5.563)
I(load)	0.005	0.002	0.008	-0.013	0.036	-0.436	-1.211
	(0.310)	(0.132)	(0.642)	(-1.435)	(0.226)	(-0.695)	(-1.118)
Constant	0.857***	0.012	0.039	-0.046***	-0.286	-6.169***	-18.828***
	(27.221)	(0.468)	(1.581)	(-3.039)	(-0.984)	(-5.130)	(-9.384)
Observations	215,948	166,869	211,622	184,639	166,545	166,298	163,749
Adjusted R^2	0.725	0.137	0.128	0.199	0.257	0.408	0.599
Time FE	Y	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y	Y
Lead Mgr FE	Y	Y	Y	Y	Y	Y	Y

Table A.5: Family characteristics of long and short horizon funds We define a fund family to be long horizon (LHF) if the value weighted average of its funds' long horizon variable (LH) is equal or greater than 0.5, or short horizon family (SHF) otherwise. The variables - Age, DC Asset ratio, Expense ratio, FPS, Turn ratio - are value weighted each month for the funds within a family; the weights are the funds' TNA in the prior month. The variable, TNA sum, is aggregated TNA among all the funds in a family. The unit of observation is family and month. Standard errors are clustered by family and by time. Only families for which at least 50% of the funds in the family have valid data for DC ratio are included for the DC ratio variable. This results in a smaller sample, which is mostly populated by small families.

Variables	LHF	SHF	LHF-SHF	*t*-stat
Age	14.897	13.167	1.730	2.64 ***
DC Asset Ratio	0.247	0.235	0.012	0.58
Expense ratio	1.067	1.259	-0.192	-5.29 ***
FPS	0.548	0.784	-0.236	-2.17 **
Aggregate TNA	7,512.27	2,854.17	4,658.10	5.49 ***
Turn ratio	67.514	77.960	-10.446	-2.14 **

A.2 Additional Details on Mutual fund fire selling

This section describes the data used to calculate mutual fund fire sales in Edmans et al. (2012). We follow the estimation approach of Gredil et al. (2022). The CRSP Survivorship Bias Free Mutual Fund database provides data at the mutual fund share class level. We use the MFLINKS file provided by Wharton Research Data Services (WRDS) to aggregate data to the fund level. For any observations not matched to MFLINKS, we use the CRSP portfolio number to aggregate the different share classes. We then merge the CRSP mutual fund database with the Thompson Financial CDA/Spectrum holdings database. We use the holdings data from CDA/Spectrum to compute the number of shares and value of equity holdings of mutual funds as of the quarter end.

Our mutual fund sample includes only equity mutual funds. Following Coval and Stafford (2007), we exclude funds with fewer than 20 holdings in the past as well as those that report the following Investment Objective Codes: international, municipal bonds, bond and preferred, or metals. We also exclude sector funds that specialize in specific industries by removing funds with Lipper classification codes AU, H, FS, NR, RE, TK, UT, CG, CMD, CS, ID, BM, or TL, or Strategic Insight codes GLD, HLT, FIN, NTR, RLE, TEC, UTI, or SEC, or Wiesenberger objective codes GPM, HLT, FIN, ENR, TCH, or UTL.

Lastly, we apply the screening criteria employed by Coval and Stafford (2007). First, to control for data discrepancies between the CDA/Spectrum equity holdings and the CRSP database, we restrict the difference between the TNA reported in the CRSP database and in the CDA/Spectrum database—$1/1.3 < (TNA_{CDA}/TNA_{CRSP}) < 1.3$). Second, we restrict changes in TNA—$-0.5 < \Delta TNA_{j,t}/\Delta TNA_{j,t-1} < 2.0$.

We closely follow Edmans et al. (2012) to construct $MFFlow$, the implied price pressure calculated by assuming that funds subject to large outflows (>5% of their assets) adjust their existing holdings in proportion to their previous portfolio weights. More precisely, we first calculate the dollar outflows of fund j from the end of quarter $q-1$ to the end of quarter q as follows:

$$Outflow_{j,q} = -(TNA_{j,q} - TNA_{j,q-1}(1 + r_{j,q})), \tag{10}$$

where $TNA_{j,q}$ is the assets under management of fund $j = 1, ..., m$, in quarter q and r is the net return of fund j in quarter q. In every quarter q, summing only over the m funds for which the percentage outflow $(\frac{Outflow_{j,q}}{TNA_{j,q-1}})$ is greater than 5%, we then construct:

$$MFFlow_{i,q} = \sum_{j=1}^{m} \frac{w_{i,j,q-1} \cdot Outflow_{j,q}}{\$Volume_{i,q}}, \tag{11}$$

where $i = 1, ..., n$ indexes stocks, $\$Volume_{i,q}$ is the total dollar trading volume of stock during quarter q, and

$$w_{i,j,q} = \frac{Shares_{i,j,q} \cdot Price_{i,q}}{\mathrm{TNA_{j,q}}}, \tag{12}$$

is fund j's holdings of stock i as a percentage of fund j's TNA at the end of the quarter.

Next, we describe the procedure used to compute the flow-induced trade (FIT) measure suggested by Lou (2012). This replication employs the same dataset as the one used for calculating the above mutual fund fire sales measure. First, we estimate the following equation from Lou (2012) to estimate the partial scaling factor (PSF) while controlling for holdings-level liquidity and other constraints:

$$trade_{i,j,q} = \beta_0 + \beta_1 \cdot flow_{j,q} + \Gamma_2 \cdot X + \Gamma_3 \cdot flow_{j,q} \cdot X + \epsilon_{i,q}. \tag{13}$$

The dependent variable is the percentage trading of stock i by fund j during quarter q. The key independent variable is $flow_{j,q}$, which is the capital flow in and out of fund j during quarter q expressed as a percentage of the fund's TNA at the end of previous quarter. X includes variables that captures liquidity and trading costs: (i) the ownership share of fund j in stock i and (ii) the effective half bid-ask spread estimated from the Basic Market-Adjusted model (Hasbrouck, 2009). These two control variables are the portfolio-weighted ownership share and liquidity cost, and therefore they are the fund level control variables. We use the above regression specification, which correspond to Columns 3 and 7 of Table 2 in Lou (2012). Based on this regression estimate, we compute $PSF_{j,q-1}$ as in Lou (2012) and use equation (14) to obtain FIT for each stock i and quarter q.

Accordingly, the 'Flow Induced Trade' measure is given as:

$$FIT_{i,q} = \frac{\sum_{j=1}^{n} w_{i,j,q-1} \cdot Outflow_{j,q} \cdot PSF_{j,q-1}}{\sum_{j=1}^{n} Shares_{i,j,q-1} \cdot Price_{i,q-1}} \tag{14}$$

where PSF is the partial scaling factor that estimates the propensity of funds to trade a stock in proportion to its beginning-of-quarter weight, estimated separately for inflows and outflows as in the specifications in columns 3 and 7 of Table 2 in Lou (2012). The summation is over all n funds that hold that stock.

There are a few differences between the two measures. First, the Lou measure includes outflows as well as inflows ($Outflow_{j,q}$ can be negative), while the Edmans et al. (2012) measure focuses only on outflows from funds that experience large outflows. Second, the Edmans et al. (2012) measure scales the flow-induced trades by contemporaneous dollar volume, whereas Lou scales by the lag of stock i's market capitalization held by mutual funds.

We convert both fire-sale measures into percentile ranks in our regression tests.

Table B.1: Data Dictionary

Variables	Description
Fund characteristics	
Assets	Assets under management in billions of dollars
Fund age	The number of years since the fund's inception
Flow	The total net assets of the fund that can be attributed to new investment, defined as [TNA(t)-TNA(t-1)*(1+r(t))]/TNA(t-1)
Turn ratio	Minimum of aggregated sales or purchases of securities divided by the average 12-month total net assets of the fund (reported annually)
Expense ratio	Expense ratio as of the most recently completed fiscal year, defined as the fraction of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees
Load	A binary variable that takes the value of 1 if a fund has a share class with non-zero load fees. See Gomez et al. (2024) for more details.
H-Horizon	The holding horizon of stock i by fund j at the end of period t is measured by $t-k+1$ for $k \leq t$ and $t \geq \theta_j$, where θ_j is the first date after the initial offer date of the fund j, or 0 otherwise. See Lan et al. (2024) for more details.
FPS	Flow-performance sensitivity of a fund. It is estimated by regressing flows onto monthly returns using 24 month rolling windows. To reduce noise, the monthly returns are calculated as the average monthly returns over the past 12 months. See Mariaseuntta and Kahraman (2017) for more details
Clientele	
DC ratio	Percentage of assets provided through defined contribution plans
Monthly returns	
Total return	The gross return of the fund as a percentage
Net return	The fund return as a percentage minus its expense ratio
Excess net return	The fund return as a percentage in excess of its benchmark return
CS	The CS measure defined in Daniel, Grinblatt, Titman, Wermers (1997)
4F alpha	The alpha of fund return in excess of the four-factor return and fund expense ratio
Monthly returns (Forward moving average)	
Total return	Geometric average of gross monthly return over the 12 months forward
Net return	Geometric average of net monthly return over the 12 months forward
Exccess net return	Geometric average of monthly return net of benchmark return over the 12 months forward
CS	Geometric average of the CS measure over the 12 months forward
4F alpha	Geometric average of the four-factor alpha over the 12 months forward

Variables	Description
Buy-Hold returns	
BHAR n	Buy-and-hold gross return minus buy-and-hold return of the benchmark index over the next n months where $n = 12, 24, 36, 48$
Additional Variables	
LH	A binary variable that takes the value 1 if a fund has evaluation horizon longer than 1 year or 0 otherwise.
ILP_LC	A binary variable that takes the value 1 if the fund arranges inter-fund lending programs or lines of credit during that year, or 0 otherwise. The data source is Form N-CEN.
MMF	Percentage of money market mutual funds (MMF) within the family; The data is from iMoneyNet (currently EPFR).
Has_MMF	A binary variable that takes 1 if a family has more than one money market fund or 0 otherwise.
Avg Mgr Tenure	The average tenure of all managers for each fund and each month since joining the fund.
Lead Mgr Tenure	Manager tenure in the industry for each fund and each month. We take the longest tenure.
Portfolio implied horizon	Following the methodology of **?**, the holding horizon of fund holdings each month. Portfolio implied horizon is adjusted by fund style.
Promotion/Demotion	Promotion at the fund level as the percentage of the managers in the fund receiving a promotion during the month. We first define manager promotion if any of the three criteria applies, (1) a manager is moving to a new fund with a larger asset, (2) the status of lead manager before and after the manager turnover, and (3) the number of funds under his management increases. The variable "Demotion" is defined similarly.
High (or Low) cum HPR (t-n,t)	A binary variable that takes 1 if a fund's holding period return in the prior n year is above (or below) the median of the holding period returns for all funds, or 0 otherwise.
I (load)	A binary variable that takes 1 if a fund offers a share class with loads or 0 otherwise; The variable 'loads' is from the CRSP Mutual Fund database. We use front and back load feeds at the fund level and select the maximum load fee that investors of the fund would pay. If the fee is missing, we regard it as 0.
ILLIQ	The Amihud measure defined in Amihud (2002) of stock; $ILLIQ_t^i = (1/Days_t^i) \sum_{d=1}^{Days_r^i} (\lvert R_{td}^i \rvert / V_{td}^i)$ where R_{td}^i is the return on day d in month t and V_{td}^i is dollar volume in millions on day d in month t. $Days_t^i$ is the number of valid observation days in month t for stock i.
Vol	The standard deviation of the idiosyncratic volatility over the past 12 months; The idiosyncratic volatility for a stock is computed by taking the stock's past return minus the expected return from the four-factor model using 24 month rolling windows.

Internet APPENDIX

Contract Evaluation Horizon and Fund Performance

July 28, 2025

Table IA.1: Fire Sale Stocks and Evaluation Horizons. Panel A reports results for the following OLS regression model:

$$\Delta shares(q+k)_{i,s,q} = \alpha + \beta_1 LH_{i,q} + \beta_2 X_{s,q} + \beta_3 X_{i,q} + \beta_4 X_q + \epsilon_{i,s,q},$$

where q is the quarter when stock s becomes a 'fire-sale' stock and the dependent variable is the change in the number of shares held by fund i in fire-sale stock s over two adjacent quarters, scaled by the stock's total number of shares outstanding. k ranges from -2 to $+3$. LH is an indicator that takes the value of one if fund i is a long-horizon fund and zero otherwise. $X_{s,q}$ captures stock characteristics such as illiquidity (ILLIQ), return momentum, size, idiosyncratic volatility over the past two years (VOL), and book-to-market ratio (BM); and $X_{i,q}$ captures fund size. Fire sale stocks are identified using the implied price pressure measure in Edmans et al. (2012). Each quarter, fire-sales stocks are those in the bottom 10 percentiles of this measure. We standardize the dependent variable using the standard deviation of all trades of funds. Panel B includes interaction terms between the LH dummy and various stock characteristics. Results are reported for the quarter following the fire-sale event. Panel C includes an interaction term between LH and the fund's flow-performance sensitivity in Column (1). In Columns (2) and (3), distressed funds are excluded from the sample. We include month fixed effects and fund style fixed effect. Standard errors are double clustered at the fund and quarter levels. t-statistics are reported in parentheses and significance levels are denoted by *, **, ***, which correspond to 10%, 5%, and 1% levels, respectively.

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)
k	-2	-1	0	$+1$	$+2$	$+3$
LH	-0.031	-0.009	0.019	0.032*	0.039*	0.015
	(-0.776)	(-0.239)	(0.950)	(1.875)	(2.010)	(0.655)
ILLIQ	0.061	0.039**	-0.007	-0.005	0.089	0.211
	(0.845)	(2.500)	(-0.611)	(-0.913)	(0.778)	(1.056)
Momentum	0.001	-0.060	-0.010	-0.025	0.017	0.005
	(-0.001)	(-1.085)	(-0.234)	(-1.258)	-0.675	-0.225
Size	-0.106***	-0.060***	-0.030***	-0.021***	-0.028***	-0.016*
	(-3.782)	(-5.966)	(-3.924)	(-3.230)	(-4.534)	(-1.719)
Vol	0.046***	0.046***	0.032***	0.021***	0.023*	0.025**
	(3.176)	(3.159)	(3.329)	(2.691)	(1.883)	(2.378)
BM	-0.012	-0.028	0.048	-0.047**	-0.025	0.066
	(-0.612)	(-1.391)	-0.78	(-2.257)	(-0.739)	(0.659)
logTNA	0.128***	0.082***	0.039***	0.009	0.012*	0.016**
	(5.031)	(5.182)	(5.553)	(1.382)	(1.883)	(2.128)
N	107,179	113,151	113,350	104,021	101,079	96,434
Adj. R^2	0.045	0.036	0.007	0.003	0.004	0.005
Style FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time

Panel B. Stock characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
k	+1	+1	+1	+1	+1	+1
LH	0.347**	-0.007	0.032*	0.005	0.031*	0.238
	(2.563)	(-0.374)	(1.884)	(0.230)	(1.802)	(1.620)
LH × Size	-0.021**					-0.017*
	(-2.588)					(-1.947)
LH × Vol		0.028**				0.015
		(2.219)				(1.264)
LH × ILLIQ			-0.001			-0.022
			(-0.044)			(-0.886)
LH × BM				0.049		0.028
				(1.355)		(0.703)
LH × MOM					0.006	0.029
					(0.160)	(0.714)
ILLIQ	-0.005	-0.005	-0.005*	-0.005	-0.005	0.001
	(-0.778)	(-0.821)	(-1.838)	(-0.695)	(-0.914)	(0.113)
Momentum	-0.025	-0.025	-0.025	-0.024	-0.029	-0.041*
	(-1.242)	(-1.237)	(-1.259)	(-1.225)	(-1.272)	(-1.960)
Size	-0.009	-0.021***	-0.021***	-0.021***	-0.021***	-0.011
	(-1.148)	(-3.227)	(-3.229)	(-3.231)	(-3.228)	(-1.432)
Vol	0.021***	0.005	0.021***	0.021***	0.021**	0.012
	(2.691)	(0.436)	(2.689)	(2.708)	(2.685)	(1.132)
BM	-0.046**	-0.046**	-0.047**	-0.073**	-0.047**	-0.061
	(-2.220)	(-2.239)	(-2.259)	(-2.075)	(-2.258)	(-1.621)
logTNA	0.009	0.009	0.009	0.009	0.009	0.009
	(1.421)	(1.377)	(1.382)	(1.388)	(1.382)	(1.417)
Constant	0.100	0.304***	0.283***	0.297***	0.283***	0.162
	(0.995)	(3.503)	(3.395)	(3.417)	(3.402)	(1.397)
N	104,021	104,021	104,021	104,021	104,021	104,021
Adj, R^2	0.003	0.003	0.003	0.003	0.003	0.003
Style FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time	Fund-Time

Panel C. Fund characteristics

	(1)	(2)	(3)
k	+1	+1	+1
		Exclude if fund flows < P10	
		Nondistressed funds	Nondistressed funds
LH	0.053**	0.029*	0.044*
	(2.081)	(1.772)	(1.952)
LH X FPS	-0.037*		-0.026
	(-1.849)		(-1.400)
ILLIQ	0.020	-0.024	-0.013
	(0.564)	(-1.529)	(-0.353)
Momentum	0.038	-0.021	0.053
	(0.839)	(-0.981)	-1.038
Size	-0.039***	-0.024***	-0.039***
	(-3.530)	(-3.671)	(-3.528)
Vol	0.030*	0.019**	0.031*
	(1.839)	(2.291)	(1.803)
BM	-0.095**	-0.033*	-0.054*
	(-2.419)	(-1.780)	(-1.836)
logTNA	0.019*	0.015**	0.025**
	(1.791)	(2.387)	(2.346)
Constant	0.482***	0.299***	0.443***
	(3.100)	(3.601)	(2.837)
N	33,506	94,105	31,339
Adj. R^2	0.006	0.003	0.006
Style FE	Y	Y	Y
Time FE	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time

Table IA.2: Money market funds as an instrument variable This table uses the percentage of money market mutual funds (MMF) within the family as an instrument variable for long evaluation contract. In the first stage, we regress the binary variable $LH(t-1)$ on $MMF(t-1)$, a percentage of MMF within the family. The first stage results are shown in Panel A Column (1). In the second stage, we utilize the second stage residual regression, following the methodology by Hausman (1978). Both the first and second stage regressions include the same control variables. The dependent variables are portfolio characteristics in Columns (2)-(3) in Panel A. In Panel B, the dependent variables are various measures of fund performances. Standard errors are clustered by fund and time. Table B.1 in the Appendix includes a detailed description of all the variables.

Panel A.

	(1)	(2)	(3)
	LH (t-1)	Turnover	Portfolio implied measure
MMF (t-1)	0.006***		
	(2.629)		
LH (t-1)		-0.039*	0.057
		(-1.857)	(1.328)
lnAssets (t-1)	0.050***	-0.040***	0.241***
	(10.060)	(-7.372)	(15.326)
Turn ratio (t-1)	0.012		-0.286***
	(1.634)		(-9.317)
Expense ratio (t-1)	-0.152***	0.005	0.133*
	(-6.330)	(0.182)	(1.960)
Flow (t-1,t)	0.074	-0.130***	-1.315***
	(1.257)	(-4.336)	(-6.746)
I(load)	0.163***	-0.007	-0.119***
	(8.588)	(-0.485)	(-3.140)
First stage residuals		-0.020	0.024
		(-1.565)	(0.461)
Constant	0.638***	0.648***	0.431***
	(25.800)	(19.032)	(5.693)
Observations	215,735	215,717	198,581
R-squared	0.448	0.872	0.555
Month FE	Y	Y	Y
Style FE	Y	Y	Y
Cluster SE	Fund-Time	Fund-Time	Fund-Time

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Net rets	Benchmark adjusted net rets	4F alpha	Total rets	Benchmark adjusted tot rets	4F alpha	DGTW	BHAR 1 year	BHAR 3 year	BHAR 5 year
LH (t-1)	0.037**	0.046***	0.002	0.037**	0.026*	0.002	0.001	0.370**	1.209**	2.723**
	(2.165)	(3.141)	(0.135)	(2.165)	(1.867)	(0.135)	(0.070)	(2.288)	(2.095)	(2.185)
lnAssets (t-1)	0.008	0.007*	0.004	0.008	0.003	0.004	0.004	0.196***	1.460***	2.996***
	(1.476)	(1.935)	(1.125)	(1.476)	(0.666)	(1.125)	(1.641)	(4.363)	(8.544)	(9.214)
Turn ratio (t-1)	-0.057***	-0.053***	-0.038***	-0.057***	-0.062***	-0.038***	-0.005	-0.695***	-1.942***	-3.030***
	(-4.409)	(-4.119)	(-3.233)	(-4.409)	(-4.027)	(-3.233)	(-0.848)	(-5.037)	(-5.206)	(-5.393)
Exp. ratio (t-1)	-0.111***	-0.103***	-0.090***	-0.111***	-0.067***	-0.090***	0.004	-0.259	-0.087	-0.274
	(-4.346)	(-5.950)	(-4.387)	(-4.346)	(-3.276)	(-4.387)	-0.282	(-1.149)	(-0.099)	(-0.169)
Flow (t-1,t)	0.008	0.064	0.299***	0.008	-0.021	0.299***	0.029	2.564***	19.332***	46.232***
	(0.061)	(0.666)	(2.907)	(0.061)	(-0.172)	(2.907)	(0.486)	(2.624)	(6.191)	(8.435)
I(load)	-0.004	0.003	0.007	-0.004	0.020*	0.007	0.001	0.044	-0.387	-0.837
	(-0.288)	(0.320)	(0.615)	(-0.288)	(1.741)	(0.615)	(0.138)	(0.338)	(-0.767)	(-0.873)
1st stage residuals	0.024	0.004	0.039**	0.024	0.037*	0.039**	0.024*	0.486**	1.813**	2.250
	(1.059)	(0.191)	(2.019)	(1.059)	(1.932)	(2.019)	(1.824)	(2.329)	(2.413)	(1.560)
Constant	0.812***	0.019	0.033	0.812***	0.046*	0.033	-0.039**	-0.011	-4.960***	-17.906***
	(26.673)	(0.780)	(1.264)	(26.673)	(1.692)	(1.264)	(-2.121)	(-0.038)	(-4.324)	(-8.228)
Observations	210,577	166,259	206,512	210,577	166,511	206,512	179,644	165,936	165,692	163,148
Adj. R^2	0.7	0.054	0.056	0.7	0.04	0.056	0.122	0.169	0.282	0.47
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y