Contract Evaluation Horizon and Fund Performance*

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PRELIMINARY - PLEASE DO NOT CIRCULATE

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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, it 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. These levers are not commonly available for mutual funds however. 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)). 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 less willing to accept these constraints. 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 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 (Binsbergen, Han, Ruan, and Xing (2023)). Broadening the scope, funds may also attract better managers via contracts that impose fewer constraints. These arguments are consistent with a large literature in corporate finance that shows that firms incentivize CEOs with compensations 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. For example, funds with long-term investors or those with lower flow-performance sensitivities should be more likely to adopt long-horizon based bonuses. Additionally, these contracts should also be more prevalent in families that are larger, more reputable, and have a more diversified asset base. These families are likely to have more resources and flexibility to provide a buffer against temporary liquidity shocks to their member funds.[1]

[1] For example, the probability of cross-trades may be higher, as well as the availability of 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.[2]

We then merge 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 the notion that 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. Finally, supporting the argument that funds with long-horizon contracts are more likely to attract talent, we show that managers with good past track records are more likely to switch to funds that offer long-horizon contracts.

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

Thus, 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 curtain 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. Additionally we show that funds with long-term investors, such as those in DC pension plans, are more likely to adopt long-term contracts, as do funds with lower flow-performance sensitivities, that is, funds that cater to more patient clients.

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 on the basis of long-horizon fund performance outperform short-evaluation-horizon funds. While our results are consistent with a voluminous literature that studies executive compensation in the corporate setting and argues that longer evaluation horizons enhance firm performance (see Edmans, Gabaix, and Jenter (2017) for a survey), they are new to the asset management literature.[3]

The principal-agent conflict in the mutual fund setting is somewhat different from that in nonfinancial firms since fund investors are also the fund's clients and the manager's compensation contract is determined by the investment adviser/fund family. 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

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

and Kahraman (2018) argue that open-end organizational structures face significant funding risk from their investors. These investors often lack the expertise to understand the fund's investment opportunities or strategy; therefore they rely on short-term performance signals to evaluate the funds. When investors vote with their feet based on recent performance, their short-sighted funding pressure discourages managers from investing in long-horizon mispricings, as such investments risk incurring losses in the short run before converging to their future payoffs (Stein (2005) and Shleifer and Vishny (1997)).

Giannetti and Kahraman (2018) provide evidence in support of managerial myopia in the mutual fund industry. They show that, for example, compared to closed-end funds, open-end mutual funds are less likely to trade against long-term mispricings. Importantly, since closed-end and open-end mutual funds are similar except for their differential exposure to investor flows, the comparison allows the authors to connect mutual fund short-termism to investors' flow-performance sensitivity. They do not consider the role of performance evaluation horizons in curtailing managerial myopia however.

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. Since restrictions such as lockups and redemption notices are not available for mutual funds, in this study we propose an alternative mechanism to insulate fund managers from short-sighted funding pressures, namely, long-horizon contracts. By doing so, we add to the asset management literature with a mechanism to alleviate managerial myopia.

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. They show that managerial compensation varies across funds and may include fixed salary as well as variable compensation. Variable compensation may be based on fund performance, assets under management, or the performance of the investment adviser/fund family. For 79% of funds in their sample, variable bonuses are tied to fund performance. They also show that fund manager compensation contracts are largely consistent with contract theory. In line with optimal contracting, for example, there are no performance differences between managers with performance-based compensation and those whose contracts do not include variable incentive pay. Ibert, Kaniel, Nieuwerburgh, and Vestman (2018) also report evidence consistent with an optimal contracting equilibrium using managerial compensation data from Sweden. Additionally, Ma et al. (2019) 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 that of enhancing fund performance. Our paper complements these recent studies by systematically investigating these roles.

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.

Although extended manager evaluation horizons enhance fund performance, fund managers are paid only on the basis of short-term fund performance in 51% of the fund-years in our sample. The cross-sectional distribution of contract horizons suggests that long-horizon contracts are more often employed by funds that cater to patient investors and fund families that are more able to absorb the temporary liquidity shocks of their member funds. Additionally, the adoption rate of long-horizon contracts among mutual funds remains very low compared to that of listed operating companies (Edmans, Gabaix, and Jenter (2017)).

Finally, our results are related to previous papers that examine the relation between investment horizon and fund performance. Investment horizon in these studies is generally inferred from fund holdings and trades. For example, Binsbergen, Han, Ruan, and Xing (2023) 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. This is consistent with the argument that funds specialize in horizon-specific skills. Similarly, Lan, Moneta, and Wermers (2023) 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 based on 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.

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 contexts 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 attacking short- or long-term mispricings will ultimately depend on the opportunities available to them.

Our findings have meaningful policy implications. The Securities and Exchange Commission adopted the initial disclosure rule on the general structure of portfolio manager compensation in 2005. 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 a tremendous amount of assets 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, in turn, 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) and manually 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 period. As described in these papers, the SAI disclosures only describe general features of the compensation contracts but not the specific amount of compensation that managers receive.

Our sample period starts in 2005 because the Securities and Exchange Commission (SEC) introduced a new rule in March 2005 that requires mutual funds to disclose the compensation structure of fund managers in the SAI.[4] Building on Lee, Trzcinka, and Venkatesan (2019), we retrieve the SAI of each fund in our sample between 2005 and 2018 from the Electronic

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

Data Gathering, Analysis, and Retrieval (EDGAR) database. We then hand-collect data on the compensation structure of mutual fund managers. Manager compensation includes a fixed salary and, in most cases, also a variable component tied to fund performance. For each fund, we create an indicator for whether it pays its managers with a variable component, and another indicator for whether the variable component is tied to fund performance. Consistent with Lee, Trzcinka, and Venkatesan (2019), we observe that most managers receive variable compensation tied to fund performance.

The SEC also requires funds to disclose the horizon over which they evaluate manager performance when determining manager pay. Thus, we are able to determine the evaluation horizon if manager pay is tied to fund performance.[5]

We then merge the compensation data to the Center for Research in Security Prices (CRSP) Mutual Fund database using ticker (or fund name when ticker is unavailable on fund SEC filings). Tickers became reliably available in fund SEC filings in 2006. The CRSP Mutual Fund database includes fund characteristics, net asset values, and returns for each share class at a daily frequency. We identify index funds based on the CRSP index fund identifiers and fund name, and exclude them from our sample.

We aggregate multiple share classes of the same fund into one fund based on the MFLINKS fund identifier or the CRSP portfolio number when the MFLINKS fund identifier is unavailable for some share classes. In particular, we sum up fund net asset value (NAV) across share classes and compute fund returns weighted by the NAV of each share class.[6] Fund stock holdings are retrieved from the Thomson Reuters Mutual Fund Holdings database and the portfolio holdings files of the CRSP Mutual Fund database for the post-2008 period (Schwarz and Potter (2016)).

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

[6]We require a share class to have at least 200 daily return observations in a year to be included in the sample for the year.

Lastly, we obtain information on fund managers from the Morningstar Direct database, and merge this database to the CRSP Mutual Fund database based on fund CUSIP number, fund ticker, or a name-matching algorithm. Our final sample includes 2,621 unique U.S. domestic equity mutual funds for the period from 2005 to 2018.

Funds usually disclose that they evaluate their managers based on multiple evaluation horizons. For example, Wellington Management discloses it pays its managers based on their 1-year and 3-year performance: "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." Interested readers can refer to EXHIBIT 1 in the Appendix for greater details of the 2012 SAI disclosures of two example funds: Wellington Management and Pioneer.

We classify each fund into each of four manager performance evaluation horizons (1, 3, 5, or 10 years) in each year based on the longest horizon disclosed in their annual disclosure. For example, we classify Welling Management as having a 3-year evaluation horizon in 2012 according to the disclosure quoted above. Almost all disclosed evaluation horizons fall into four values: 1, 3, 5, or 10 years. Yet there are 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 reported evaluation horizons of 4 years to 5 years. There are 59 such cases in total.[7]

Figure 1 plots the number of funds in our sample by manager evaluation horizon and for each year from 2005 to 2018. These numbers are also presented in Table 1. We observe that the 1-year evaluation horizon is the most popular, being adopted in 51.2% of the 22,047 fund-years in our sample. The adoption rates are 20.0% for the 3-year horizon, 25.6% for the

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

5-year horizon, and merely 3.1% for the 10-year horizon. That is, the majority of the mutual funds pay their managers with variable bonus based on only the fund's 1-year performance, in sharp contrast to the fact that nearly all corporate executives' compensations are tied to long-run corporate performance (Edmans et al. (2017)).

We are able to identify manager compensation for 1,156 funds in 2005 and 2006, the first two years funds were required to disclose such information. The number of funds that disclose manager evaluation horizons jumped to 1,986 in 2007 and steadily dropped to 1,406 in 2018, the end of our sample period. Funds with longer evaluation horizons were more likely to disclose their compensation structure in 2005-2006, in which the adoption rate of the 1-year horizon contract was 42.9%. The adoption rate of the 1-year evaluation window has always been above 50% since 2007, remaining stable with 54.1% in 2007 and 53.1% in 2018. Meanwhile, the adoption rate of the 3-year horizon more than halved from 19.8% in 2007 to 9.2% in 2018, that of the 5-year horizon rose from 23.1% to 33.7%, and that of the 10-year horizon slightly increased from 3.0% to 4.0% over the same period.

Table 2 reports descriptive statistics at the level of fund-month. Panel A summarizes the characteristics of the sample funds. In Panel B, we divide the funds into 'long-horizon' and 'short-horizon' funds. A 'short-horizon' fund has a 1-year manager evaluation horizon, while a 'long-horizon' fund has manager evaluation horizons longer than 1 year. We follow this classification for the rest of the analyses in the paper. We provide a comprehensive data dictionary in Table A.1 in the Appendix.

Column (5) of Panel B compares the characteristics of long- and short-horizon funds and tests whether the difference between the two groups is statistically significant. The results show that funds with long-horizon evaluation contracts are significantly larger and older, for example. They also have lower turnover and hold larger and less concentrated portfolios.

Importantly, we also expect that funds that serve more patient investors are more likely to use bonuses tied to long-horizon fund performance. Specifically, the table includes two proxies for investor patience. Our first measure is the fund's flow-performance sensitivity, which we estimate using 24-month rolling window regressions that regress monthly fund flows[8] on the prior 12 month average monthly return of the fund. Since defined contribution (DC) plan investors invest their retirement savings for the long-term, our second approach to measure the patience of the fund's clientele is by using the DC assets under management of the fund.

In terms of clientele, the table confirms that long-horizon funds manage more retirement assets and have lower flow-performance sensitivities. This indicates that they have more patient investors. Finally, they also have higher average returns. These univariate results are consistent with our hypotheses discussed above. In the following section, we extend our analyses to the multiple regression setting to provide a more comprehensive picture.

3 Results

3.1 Manager Compensation and Portfolio Characteristics

The main hypothesis in this paper is that compensation contracts that include bonuses tied to the long-term performance of the fund insulate the manager from the short-term pressure of their investors. Therefore, these contracts can restore managers' incentives to trade on long-term mispricing. We now examine the characteristics of fund holdings and trades to test whether managers with long-horizon contracts are more likely to pursue long-term investment strategies.

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

3.1.1 Portfolio Characteristics

We begin by examining the relation between performance evaluation horizon and various portfolio characteristics, specifically, turnover, portfolio size, and the portfolio share of the fund's top ten holdings. Specifically, we regress these variables one-by-one on an indicator variable that takes the value of one if the fund is a long-horizon fund and zero otherwise. In these tests, we control for (the natural logarithm of) fund size, fund age, fund turnover, expense ratio, and fund flow measured at the end of the last month. Additionally, the models include style and fund-month dummies and the standard errors are two-way clustered by fund and time. The unit of observation is fund-month.

Table 3 reports the results. The table shows that long-horizon funds have significantly lower turnover (columns (1)-(2)). This confirms that long-horizon funds hold positions longer. Additionally, they hold a larger, more diversified portfolio (columns (3)-(6)). These differences are statistically significant, and the economic magnitudes of the differences are modest and reasonable. For example, compared to the unconditional turnover of long-horizon funds, the turnover of short-horizon funds is only about 4% (=0.029/0.737) higher. This is not surprising as our long-horizon labels simply identify whether managers are incentivized to also consider attacking long-term mispricings, as mentioned above. It also illustrates that our horizon sorts are very different from the revealed horizon sorts utilized in previous studies (for example, Lan, Moneta, and Wermers (2023) and Binsbergen, Han, Ruan, and Xing (2023)). Similarly, compared to the unconditional number of stock holdings of long-horizon funds, the number of stock holdings of short-horizon funds is about 4% (=0.172/4.549) smaller. On the other hand, the level of portfolio concentration, measured as the ratio of the fund's top 10 stock holdings to fund NAV, is about 14% (=0.040/0.287) higher for short-horizon funds than their long-horizon peers.

In sum, long-horizon funds trade less frequently and hold more diversified portfolios than short-horizon funds, which is consistent with the hypothesis that extended manager performance evaluation horizons help insulate the manager from the short-term pressure of their investors.

3.1.2 Long Horizon Funds' Trading in Fire Sale Stocks

In this section, we examine whether funds with long evaluation horizons are more likely to engage in long-horizon arbitrage strategies. To identify securities with periods of long-term mispricing, we follow Giannetti and Kahraman (2018) and turn to transitory shocks to equity prices resulting from fire sales by mutual funds. The fire-sale approach is motivated by the observation that extreme outflows are more likely to force managers to liquidate assets, thereby generating significant price pressure. Coval and Stafford (2007) show that stocks subject to fire sales suffer a substantial transitory decline in prices, which can persist for several quarters. Therefore, trading against flow-induced mispricing is a profit opportunity over the long run but not necessarily over the short run.

A potential concern with using actual fire sales to measure transitory shocks is that mutual fund managers have discretion about which stocks to sell in response to redemption requests. For this reason, we closely follow the approach in Edmans, Goldstein, and Jiang (2012, EGJ) and Gredil et al. (2022) 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:

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

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:

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

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

$$w_{i,j,q} = \frac{Shares_{i,j,q} * Price_{i,q}}{\mathrm{TNA_{j,q}}}, \tag{3}$$

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

We also construct the Lou (2012, Lou) 'Flow Induced Trade' measure:

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

where PSF 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). $Flows$ is the capital flow to fund i during quarter q expressed as a percentage of the fund's lagged TNA, and $shares$ is the number of shares held by fund i as of the end of the previous quarter. Additional details regarding the construction of both measures are in the Appendix A.1.

The two measures of fire sale differ from each other on at least two aspects. First, *FIT* considers both fund inflows and outflows, while *MFFlow* focuses on outflows. Second, *MFFlow* scales flow-induced trades by contemporaneous dollar trade volume, but *FIT* does not. Scaling by dollar volume is motivated by the idea that a larger volume can absorb a more intense selling pressure without a significant price impact, *ceteris paribus*. Hence, *MFFlow* may deliver deeper transitory price shocks.[9] We employ both measures in our analysis and

[9]On the other hand, Wardlaw (2020) argues that scaling by contemporaneous dollar volume may make $MFFLow$ mechanically related to returns in the event quarter. Lou (2012) also finds evidence that mutual fund sales result in transitory price pressure that eventually reverses.

observe consistent results based on them, which alleviates the concern that our findings are mechanical or spurious.

We convert both fire-sales measures into percentile ranks in our regression tests. Each quarter, stocks with *MFFlow* (or *FIT*) below the tenth percentile are regarded as fire sale stocks. In unreported results, we confirm that stocks under severe selling pressure indeed experience large price decreases that revert back to the original level over the subsequent 6 to 8 quarters. The magnitude of price pressure resulting from fire sales in our sample is comparable to that documented in Edmans et al. (2012).

Following Giannetti and Kahraman (2018), to examine how the evaluation horizon in the compensation contract affects fund trading behavior, we estimate the following regression model for all fire-sale stocks:

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

where q is the fire-sale quarter and k ranges from -2 to +3. The dependent variable is the change in the number of shares held by fund i in security s over two adjacent quarters. We standardize the dependent variable by dividing it by the total number of shares outstanding. LH is a dummy 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). Following Giannetti and Kahraman (2018), the $X_{s,q}$ and $X_{i,q}$ matrices capture stock and fund characteristics. Stock characteristics include illiquidity (ILLIQ), momentum, size, idiosyncratic volatility over the past two years (VOL), and book to market value (BM). Fund characteristics include fund size as measured by the natural logarithm of the fund's TNA (logTNA). We also include time fixed effects to control for unobservable market-wide trends. We cluster standard errors by fund and by time.

Panel A of Table 4 presents the regression results. Interestingly, we do not observe a statistically significant difference in the trading behavior for fire-sale stocks between short- and long-horizon managers before the fire-sale event quarter t. However, during the subsequent two quarters after the fire-sale event, managers with a long evaluation horizon aggressively take advantage of the flow-driven mispricing opportunities and add more fire-sale stocks to the portfolio. 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. It is interesting to observe a similar level of trading intensity over the next two quarters. These results are based on fire sale stocks identified using *MFFlow*. As a robustness check, we also identify fire sale stocks using *FIT* and find qualitatively similar results. These results are displayed in Table A.3 in the Appendix.

Next, in Panel B of Table 4, we zero in on the time period right after the fire-sale quarter and examine the characteristics of fire-sale stocks preferred by long-horizon fund managers. The working hypothesis in this panel is that trading differences between long- and short-horizon funds should be larger when the arbitrage risk of the fire-sale stock is higher (Shleifer and Vishny (1997)). For instance, Giannetti and Kahraman (2018) argue that small stocks and those with high idiosyncratic volatility are securities with high arbitrage risk.

The first two columns of Panel B provide evidence consistent with these economic priors. In column one, the coefficient for the two-way interaction term between *LH* and *Size* is negative and statistically significant, indicating that differences in trading behavior between long- and short-horizon funds are smaller (larger) when the fire-sale stocks are larger (smaller). Similarly, if stocks with high idiosyncratic volatility are considered to carry high arbitrage risks (Pontiff (2006)), we expect short-horizon funds to be reluctant to trade against mispricing in high idiosyncratic volatility stocks, while the opposite argument can be applied to long-horizon funds. The coefficient for the two-way interaction term between LH and Vol in the second column confirms this conjecture.

In the remaining columns, we examine other characteristics, such as iliquidity, Book to Market ratio, and momentum, but none of them is significantly related to fire-sales trades conducted by long-horizon funds. These results are consistent with the features of holdings preferred by closed-end funds in Giannetti and Kahraman (2018).

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-sales events. In the final part of this section we show that long-horizon funds load more heavily on long-term risk using the equity term structure.

In a recent paper, Gonçalves (2021) argues that although news about discount rates may not fully summarize investment opportunities as suggested by the model in Campbell (1993), the full term structure of equity-strip expected returns does. This is because it captures investment opportunities at different horizons. In particular, two state variables that describe investment opportunities over 1 year or longer 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 the 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. This in turn requires information on fund dividends. While daily dividend reports are available for funds, the quality of the data is known to be noisy with reported dividends often exceeding dividends reported in the annual report. Therefore, we follow Harris, Hartzmark, and Solomon (2015), and use annual summary reports from CRSP.

Our detailed methodology is as follows. We decompose fund returns $\tilde{r}_t$ into a portfolio of equity strip returns, $\tilde{r}_t^{(h)}$, as follows:

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

The equity strip returns over the h years 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 equation 7. Finally, we estimate the equity strip returns, $\tilde{r}_h^{(h)}$ by using the transformation matrix Φ, the residual state vector $\tilde{z}_t$ (equation 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 equation 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 reports the cumulative loadings of long- and short-horizon funds on dividend strips. While short-horizon funds tend to have significantly larger loadings on the shortest risk horizon, long-horizon funds load more heavily on long-horizon risk. Specifically, long-horizon funds have a cumulative loading of 0.224 on short-term (one to five years) dividend strips, compared to 0.275 for short-horizon funds. The difference in the loadings is statistically significant at the one percent level.

Using the Gonçalves (2021) approach, we also estimate the average duration of long- and short-horizon funds. We find that the average duration of long-horizon funds is approximately 8% higher than that of short-horizon funds, and the difference is statistically significant.

3.2 Manager Compensation and Fund Performance

The results in the previous section suggest that managers who are evaluated based on long-horizon performance are more likely to invest in long-term investment opportunities. We now turn to fund performance.

We begin our analyses by focusing on *stock-level* performance: by comparing the performance of the stocks included in long- and short-horizon fund portfolios. To do so, we divide stocks into quintiles each month based on whether they are largely held by short-horizon funds (quintile 1) or by long-horizon funds (quintile 5). We then calculate the value-weighted Fama-French three factor-adjusted stock returns for each group for up to 5 years in the future.

Figure 2 provides a graphical representation of the return differences for each future holding period. The results show that stocks that are largely held by long-horizon funds (quintile 5) have sigificantly higher returns than those in quintile 1, which are largely held by short-horizon funds. This return difference is robustly significant for each of the five holding periods in our table. This is consistent with the idea that long-horizon contracts alleviate investment constraints and thus increase managers' investment opportunities. In contrast, peer managers with short-horizon contracts are not only limited to opportunities with short-term payoffs, but short-term opportunities are also less scalable (Binsbergen, Han, Ruan, and Xing (2023)). Therefore we expect long-horizon managers to outperform those without these contracts.

To more rigorously test this argument, we now provide additional performance analyses at the *fund-level*. To do so we use several performance measures to compare our long- and short-horizon funds. Specifically, we use both the monthly net-of-fee return of the fund and its monthly gross return. We then also adopt risk-adjusted net and gross returns using several approaches. First, we risk-adjust returns by calculating monthly net and gross returns in excess of the benchmark returns of the fund. We obtain benchmark information from the Morningstar database, where the benchmark is the self-designated index disclosed in each fund's prospectus.

Second, we also risk-adjust net-of-fee and gross returns using the Carhart (1997) four-factor model. To calculate the Carhart alphas for month t, we estimate the four-factor model using data on monthly fund returns and factor returns for the market, size, book-to-market, and momentum factors over 24-month rolling windows ending in month $t-1$.

Finally, we use the average monthly benchmark-adjusted excess return of the stocks in the fund's portfolio as in Daniel, Grinblatt, Titman, and Wermers (1997) ('DGTW') and Wermers (2004). The DGTW benchmark adjustment procedure sorts stocks into size quintiles, and within each size quintile stocks are further sorted into bookto-market quintiles. Finally, each book-to-market quintile is divided into five momentum portfolios. The sorting process creates 125 stock characteristics groups, for which benchmark portfolios are formed by calculating the value-weighted average return of the stocks in each category. Finally, with each of the DGTW benchmark portfolio returns, we calculate the characteristic-adjusted returns by subtracting from each stock's return the value-weighted average return of stocks with similar size, book-to-market, and momentum characteristics as defined by the triple-sort benchmark portfolios. Since the DGTW-adjusted returns use the stocks in the fund's portfolio, fund fees are not included in calculating these returns.

Table 6 summarizes the results. Each column in the table uses one of the fund returns described above as the dependent variable of the regression. The fund returns are expressed in percentages. Panel A reports the results from regressing the various fund returns on an indicator variable that takes the value of one if the fund is a long-horizon fund and zero otherwise. We include style and year-month dummies and the standard errors are two-way clustered by fund and time. The unit of observation is fund-month. In Panel B, we add fund characteristics as additional controls. These are analogous to the controls used in the previous tables and include the natural logarithm of fund size, the natural logarithm of fund age, the fund's turnover ratio, the expense ratio, and fund flow.

We find very similar results across the two panels. We consistently find that long-horizon funds exhibit significantly higher returns than their short horizon peers. This is true with or without risk-adjustments and also both for net and gross returns. For example, we find that the above benchmark performance of long-horizon funds is approximately 60 basis points higher than that of short-horizon funds.

In Table 7, we replace our monthly fund return measures with buy and hold returns fund returns net of the buy and hold returns of the fund's benchmark over the next one year, next three years, and next five years. Analogously to Table 6, we report the results without fund-characteristics controls in Columns (1)-(3), but add these controls in Columns (4)-(6). The table shows that long-horizon funds deliver significantly larger above-benchmark returns over all three holding horizons relative to short-horizon funds. Long-horizon funds outperform short-horizon funds by 64 basis points in the next year, and the outperformance accumulates to 2.2% and 4.2% over the next three and five years, respectively.

Finally, to provide additional robustness, we reproduce our performance results using matched samples of mutual funds. We adopt two matching approaches. The first approach minimizes the Gaussian distance of fund characteristics, while the second approach is based on propensity score matching. Our matching methods use 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. Gaussian matching provides a better match for each fund, however it results in a smaller sample.

The results are tabulated in Table A.2 in the Appendix. The table shows that the performance results are robust to our matched-sample methodology. All coefficient estimates reported in Tables 6 and 7 remain statistically significant. Additionally, the economic magnitudes are also largely unaffected.

3.3 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 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 alleviate the short term funding costs imposed by investor withdrawals. They simply assure that managerial compensation is not directly affected by these costs. This in turn restores managers' incentives to consider long-horizon opportunities.

Since the fund and, ultimately, the family still bear the cost of investors' short-term flow-performance sensitivity, not all families can offer these contracts. Consistent with the argument that these contracts should be more prevalent in funds that are larger, more reputable, and have a more diversified asset base, our earlier fund-level descriptive statistics in Table 2 confirm that long-horizon funds are indeed larger and older. Table 2 also shows that funds with long-horizon contracts have lower flow-performance sensitivites and manage more defined contribution (DC) retirement assets, suggesting that they manage assets for more patient investors.

This is also true for fund families. Specifically, we report *family-level* univariate summary statistics in Table 8 to provide a comparison of the characteristics of long- and short-horizon families. In these tests, we classify a family as a long-horizon family if more than 50% of its assets are managed by funds whose managers receive a long-horizon contract. The table shows that long-horizon families are considerably larger. Moreover, they are older and manage a larger number of funds, suggesting that they are likely to have more resources and flexibility to provide a buffer against temporary liquidity shocks to their member funds. Importantly, Table 8 shows that the flow-performance sensitivity of the average fund is significantly lower in long-horizon families. Long-horizon families also manage more DC retirement assets, although the difference is not statistically significant.

While Tables 2 and 8 offer support at the univariate level, we next examine how contract horizon is related to fund and family characteristics in the regression framework. Specifically, in Table 9, we examine the likelihood that a fund has a long evaluation horizon. The results in the table are based on a linear probability model where the dependent variable takes the value of one if the fund has a long evaluation horizon or zero otherwise. Our independent variables of interest are the variables we highlighted above, such as the fund's estimated flow-performance sensitivity, the percentage of the fund's assets contributed by defined contribution plans (*DC asset ratio*), age, and size.

Column (1) in the table shows that funds with lower flow-performance sensitivities are more likely to offer long-horizon contracts. Similarly, Column (2) indicates that the percentage of DC assets under management is strongly positively related to the choice of long evaluation horizons. Additionally, consistent with the univariate statistics, funds that are older and larger are more likely to offer these contracts.

Finally, in Column (6) we examine the role of interfund lending. As we argue above, we expect that funds in families with resources to provide a buffer against temporary liquidity shocks are more able to offer long-horizon contracts. Up to this point, variables such as size, age, or the number of funds in the family are used to proxy for these funds. In a first step to directly capture the availability of liquidity pools within the family, we collect information from Form N-CEN on interfund lending. Unfortunately, Form N-CEN is only available at the very end of our sample period (i.e., in 2018), therefore the analyses in Column (6) only use a small subsample. Despite the sample limitation, we find that funds with access to interfund lending facilities are significantly more likely to offer long-horizon contracts.

3.4 Do Long Evaluation Horizon Funds Hire Better Managers?

In Section 3.1 we show that managers with long-horizon contracts are less constrained and consequently, they are more likely to trade against long-term mispricings or hold portfolios with higher loadings on long-term risk. We also argue that this is an important economic channel behind the superior performance of long-horizon funds. In this section we examine an additional channel that may arise from lower managerial constraints. Specifically, we ask whether funds are able to attract more talented managers by offering long-horizon contracts.

To test this hypothesis, we obtain the employment history of fund managers from Morningstar. Morningstar assigns fund managers a unique identifier and specifies their starting and departing dates for each fund. This allows us to cleanly capture managerial turnover. We identify 2,208 fund manager turnovers during our sample period.

To examine the role of the evaluation horizon in attracting talent, we model the determinants of the length of a manager's contract horizon at the new fund. Accordingly, our dependent variable in these analyses is the contract evaluation horizon the manager receives at the new fund (measured as the maximum evaluation horizon listed in the SAI, as mentioned above). We use this more granular measure, rather than the binary variable *Long Horizon* used in the previous analyses, to more finely capture increases/decreases in the manager's contract horizon around managerial turnovers. Our main explanatory variable of interest is the manager's performance at the previous fund. To measure the performance, we take the value-weighted average of the benchmark adjusted returns of all the funds the manager manages each month and compute their moving average over 36 (or 60) months.

Table A.4 reports the regression results. The table shows that across the manager turnovers in our sample, better performance at the previous fund enhances managers' chance to move to a new fund that offers a longer performance evaluation horizon. Additionally, the results reveal that the manager's evaluation horizon at the previous fund matters as well and strongly predicts the chance of having a longer evaluation horizon at the new fund. These findings are robust to controlling for unobservable characteristics of the former fund through fund fixed effects in Columns (5) and (6), or those of the manager through manager fixed effects in Columns (7) and (8).

3.5 Robustness

3.5.1 Holdings Implied Horizon vs. Contract Horizon

Finally, previous studies (for example, Lan, Moneta, and Wermers (2023) and Binsbergen, Han, Ruan, and Xing (2023)) 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: 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, whether these less-constrained managers end up attacking short- or long-term mispricings will ultimately depend on the opportunities available to them.

We now formally compare our horizon classification to that in Lan, Moneta, and Wermers (2023). Specifically, we follow the methodology in Lan et al. (2023) to calculate their proposed point-in-time horizon measure, holding horizon ('H-H'). As described by the authors, H-H in month t is the value-weighted holding period of the securities included in the fund's portfolio at the end of the month. The final measure is style adjusted by subtracting from each fund's H-H the average H-H of the funds that have the same investment style.

We find that fund H-H is higher for long-horizon funds. Not surprisingly however, the correlation between our long-horizon indicator and the H-H measure is only 3.2%. In Table A.5 in the Appendix we re-estimate Table 6 by including H-H as an addition explanatory variable. The results show that long-horizon funds continue to outperform short-horizon funds in this specification, indicating that the fund's implied holding horizon does not drive our results.

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. 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.

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Figure 1: Number of Funds with Long and Short Evaluation Horizons This figure plots the annual number of sample equity funds with different manager evaluation horizons in each year from 2005 to 2018. Fund firms are required to disclose their compensation structure starting from 2005. Disclosures with specific lengths of manager performance evaluation horizons were less common in the first two years due to the lack of standard disclosure guidelines.

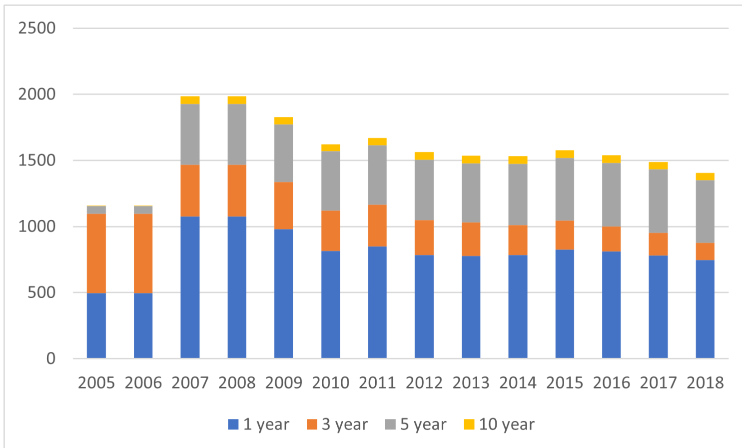

Figure 2: Returns of Common Holdings of Long-Horizon and Short-Horizon Funds Each month we sort stocks held by both long-horizon funds and short-horizon funds into five quintiles based on [...]. Short-horizon (long-horizon) funds pay their managers based on the fund's one-year (longer than one year) performance. The graph displays the mean and [...] of the Fama-French three-factor α of stocks in the first quintile (i.e., stocks favored by short-horizon funds) and stocks in the 5th quintile (i.e., stocks favored by short-horizon funds) over the next N (= 1, 2, 3, 4, or 5) years after the sorting month. The returns represent future returns over various horizons calculated using a 24-month rolling window.

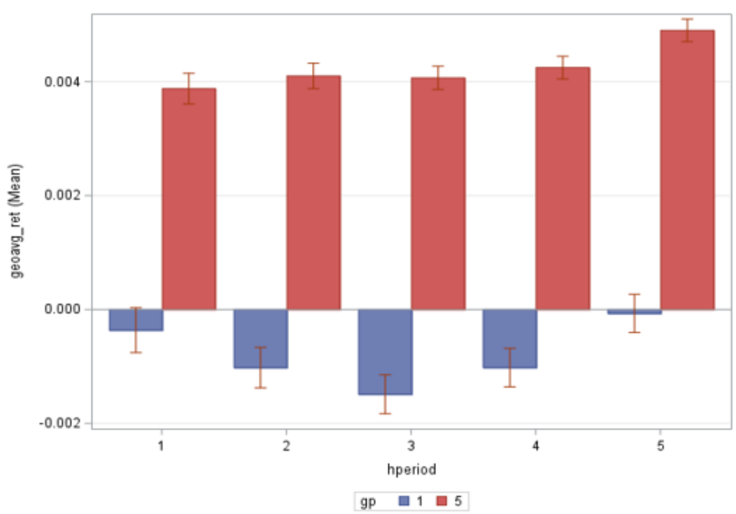

Table 1: Number of Funds with Long and Short Evaluation Horizons This table presents the annual number of sample equity funds with different manager evaluation horizons in each year from 2005 to 2018. Fund firms are required to disclose their compensation structure starting from 2005. Disclosures with specific lengths of manager performance evaluation horizons were less common in the first two years due to the lack of standard disclosure guidelines. Our sample includes 2,621 unique U.S. equity mutual funds.

Year	# funds	1 year	3 years	5 years	10 years
2005	1,156	496	600	59	1
2006	1,156	496	600	59	1
2007	1,986	1,075	393	459	59
2008	1,986	1,075	393	459	59
2009	1,827	979	359	436	53
2010	1,622	814	308	447	53
2011	1,670	851	313	450	56
2012	1,564	783	265	457	59
2013	1,535	777	253	447	58
2014	1,533	784	228	464	57
2015	1,579	827	220	472	60
2016	1,539	813	187	480	59
2017	1,488	781	171	480	56
2018	1,406	746	130	474	56
All	22,047	11,297	4,420	5,643	687

Table 2: Descriptive Statistics This table reports descriptive statistics. The unit of observation is fund-month. Panel A describes the characteristics of the funds in the sample. In Panel B, we divide our sample into 'long-horizon' and 'short-horizon' funds. A fund is a 'Long-horizon' fund if the evaluation horizon used to determine the manager's performance bonus pay is longer than one year. Similarly, the 'short-horizon' group captures funds for which the manager evaluation horizon is one year or shorter. We provide a comprehensive data dictionary in Table A.1 in the Appendix. $***$, $**$, and $*$ indicate statistically significance at the 1%, 5%, and 10% level, respectively.

Panel A. Fund Characteristics

	N	Mean	SD	P25	P50	P75
Assets (in $ billions)	153,795	1.569	5.410	0.079	0.304	1.133
Fund age	153,698	15.079	11.616	7.954	12.507	18.345
Fund flow	150,744	0.149	0.617	-0.486	-0.006	0.952
Fund turnover ratio	152,701	0.753	0.829	0.310	0.570	0.946
Expense ratio	147,649	0.011	0.004	0.009	0.011	0.013
Log # of stocks	153,795	4.412	0.746	3.912	4.331	4.779
Top10 holdings	107,846	0.305	0.131	0.219	0.290	0.369
Flow-perf sensitivity (FPS)	146,673	0.588	3.201	-0.265	0.209	0.994
DC ratio	35,776	0.205	0.148	0.075	0.181	0.311
Gross monthly return (%)	150,680	0.721	4.529	-1.780	1.201	3.700
Net monthly return (%)	150,678	0.629	4.529	-1.871	1.111	3.610
Benchmark-adj return (%)	134,139	-0.104	1.372	-0.851	-0.086	0.655
DGTW-adj return (%)	150,297	-0.002	1.120	-0.617	0.025	0.656

Panel B. Difference between Long and Short Evaluation Horizon Funds

	Long N	Short N	Long Mean	Short Mean	LH-SH Diff	
Assets (in $ billions)	82,043	71,752	2.166	0.887	1.279	***
Fund Age	81,963	71,735	15.982	14.048	1.933	***
Fund flow	80,575	70,169	0.150	0.148	0.002	***
Fund turnover ratio	81,175	71,526	0.737	0.772	-0.036	***
Expense ratio	78,478	69,171	0.011	0.012	-0.001	***
Log # of stocks	76,309	62,738	4.549	4.422	0.127	***
Top10 holdings	60,090	47,756	0.287	0.329	-0.042	***
Flow-perf sensitivity (FPS)	76,450	65,685	0.521	0.646	-0.125	**
DC ratio	24,624	10,589	0.215	0.183	0.032	***
Gross monthly return (%)	80,497	70,183	0.762	0.674	0.088	***
Net monthly return (%)	80,499	70,179	0.674	0.578	0.096	***
Benchmark-adj return (%)	72,474	61,665	-0.076	-0.137	0.061	***
DGTW-adj return (%)	80,614	69,683	0.010	-0.016	0.026	***

Table 3: Evaluation Horizon, Fund Turnover, Portfolio Size and Top 10% Holdings. This table presents OLS regression results where the dependent variables are as follows: Columns (1)-(2), fund turnover ratio; Columns (3)-(4), portfolio size measured as the natural logarithm of the number of stocks in the fund's portfolio; and Columns (5)-(6), top 10 % holdings, which is the aggregate value of the fund's top 10 holdings as a fraction of the fund's net asset value. The key independent variable of interest is 'Long horizon', which takes the value of 1 if the evaluation horizon used to determine the manager's performance bonus pay is longer than one year, and 0 otherwise. The control variables are the natural logarithm of the fund's NAV (in $Billion), the natural logarithm of fund age (in years), fund turnover ration, fund expense ration, and fund flow. The explanatory variables are lagged by one month relative to the dependent variable. We control for time and fund style fixed effects, and cluster standard errors by time and fund. Variable definitions are offered in Table A.1 in the Appendix. Reported in parentheses are t-statistics. $***$, $**$, and $*$ indicate statistically significance at the 1%, 5%, and 10% level, respectively.

	(1) Turnover	(2) Turnover	(3) Portfolio Size	(4) Portfolio Size	(5) %Top10 Hldgs.	(6) %Top10 Hldgs.
Long horizon (t-1)	-0.029^{**}	-0.025^{**}	0.172^{***}	0.079^{**}	-0.040^{***}	-0.037^{***}
	(-1.966)	(-2.135)	(5.453)	(2.521)	(-5.924)	(-5.378)
lnAssetsB (t-1)		-0.040^{***}		0.080^{***}		0.001
		(-7.287)		(7.737)		(0.122)
lnAge (t-1)		0.030^{**}		-0.060^{***}		0.014^{**}
		(2.398)		(-2.819)		(2.437)
Turnover ratio (t-1)				0.092^{***}		-0.015^{**}
				(4.329)		(-2.357)
Exp ratio (t-1)		-0.017		-0.315^{***}		0.033^{***}
		(-0.581)		(-7.616)		(2.987)
Flow (t-1, t)		-0.017		0.078		-0.025^{**}
		(-1.143)		(1.265)		(-1.996)
Constant	0.767^{***}	0.657^{***}	4.321^{***}	4.891^{***}	0.327^{***}	0.264^{***}
	(57.082)	(15.258)	(174.387)	(66.409)	(57.385)	(12.443)
N of obs.	152,084	148,863	147,477	140,062	107,903	103,749
Adj. R^2	0.023	0.864	0.026	0.109	0.04	0.059
Time FE	Y	Y	Y	Y	Y	Y
Style FE	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

Table 4: Fire Sale Stocks and Evaluation Horizons. 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 Edmans et al. (2012). The variable k refers to the quarter relative to the fire sale quarter, varying from -2 to $+3$. Panel B examines evaluation horizons and the characteristics of fire sale stocks. The description of the variables is included in Table A.1 in the Appendix.

Panel A. Long and short horizon funds

	(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 of Obs.	108,801	114,965	115,231	105,643	102,689	98,135
Adj. R^2	0.046	0.037	0.008	0.004	0.004	0.005
Time FE	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

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	−0.030	−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 of obs.	105,643	105,643	105,643	105,643	105,643	105,643
Adj. R^2	0.004	0.004	0.004	0.004	0.004	0.004
Time FE	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

Table 5: Cumulative Fund Loadings on the Equity Strips This table shows the funds' loadings onto the horizon-specific risks. We follow the methodology of Gonçalves (2021) to construct the equity strips, which consist of a set of risks over various horizons.

Risk horizon h	LH	SH	Diff (LH-SH)
[1, 5]	0.2240	0.2747	-0.0507^{***}
[6, 20]	0.2659	0.2542	0.0117^{**}
[6, 30]	0.4365	0.4113	0.0253^{***}
[6, 40]	0.6063	0.5682	0.0381^{***}
[6, 50]	0.7760	0.7253	0.0507^{***}

Table 6: Fund Performance and Evaluation Horizon I. This table presents OLS regression results where the dependent variables are: (1) monthly net fund return; (2) monthly net fund return in excess of the benchmark return; (3) monthly alpha based on net fund return; (4) monthly gross fund return; (5) monthly gross fund return in excess of the benchmark return; (6) monthly alpha based on gross fund return; (7) DGTW-adjusted fund return. Fund alpha in month t equals $R_t - \beta_{t-1} \times F_t$, where R_t is the fund's net (gross) return, F_t is the vector of the Carhart four factors, and β_{t-1} is fund β on the Carhart four factors estimated using the fund's month net (gross) returns over the last 24 months. Panel A reports regression results where there is only one independent variable: 'Long horizon', which takes the value of 1 if the evaluation horizon used to determine the manager's performance bonus pay is longer than one year, and 0 otherwise. In Panel B, we add additional control variables to the regressions, including the natural logarithm of the fund's NAV (in $Billion), the natural logarithm of fund age (in years), fund turnover ration, fund expense ration, and fund flow. The explanatory variables are lagged by one month relative to the dependent variable. Variable definitions are offered in Table A.1 in the Appendix. We control for time and fund style fixed effects, and cluster standard errors by time and fund. Reported in parentheses are t-statistics. $***$, $**$, and $*$ indicate statistically significance at the 1%, 5%, and 10% level, respectively.

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Long horizon (t-1)	0.076***	0.059***	0.033**	0.067***	0.051***	0.023*	0.021***
	(5.818)	(6.934)	(2.348)	(5.196)	(6.104)	(1.669)	(3.333)
Constant	0.565***	−0.149***	−0.126***	0.659***	−0.055***	−0.028**	−0.031***
	(62.371)	(-23.288)	(-10.694)	(73.721)	(-8.963)	(-2.433)	(-6.444)
N	154,566	136,965	93,506	154,565	136,967	93,506	157,432
Adj. R^2	0.782	0.056	0.022	0.782	0.056	0.023	0.143
Time FE	Y	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y	Y

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Long horizon (t-1)	0.068***	0.049***	0.030**	0.068***	0.050***	0.030**	0.021***
	(5.942)	(5.928)	(2.345)	(5.925)	(6.016)	(2.322)	(3.169)
lnAssetsB (t-1)	−0.004	−0.002	−0.007	−0.004	−0.002	−0.007	−0.001
	(-0.790)	(-0.769)	(-1.522)	(-0.744)	(-0.834)	(-1.496)	(-0.405)
lnAge (t-1)	−0.003	0.014**	0.020	−0.003	0.015**	0.020	0.010**
	(-0.312)	-2.396	-1.561	(-0.331)	(2.532)	(1.576)	(2.023)
Turnover ratio (t-1)	−0.046***	−0.046***	−0.029***	−0.046***	−0.047***	−0.030***	−0.007
	(-3.559)	(-4.654)	(-2.944)	(-3.598)	(-4.826)	(-2.985)	(-1.214)
Exp ratio (t-1)	−0.069***	−0.086***	−0.099***	0.007	−0.016	−0.019	−0.015
	(-3.175)	(-6.638)	(-4.595)	(0.315)	(-1.149)	(-0.862)	(-1.502)
Flow (t-1,t)	0.083	0.049	0.104**	0.084	0.050	0.103**	0.025
	(1.161)	(1.250)	(2.147)	(1.187)	(1.265)	(2.135)	(0.553)
Constant	0.654***	−0.057***	−0.065*	0.661***	−0.046**	−0.063*	−0.037**
	(19.359)	(-2.676)	(-1.797)	(19.651)	(-2.125)	(-1.737)	(-1.994)
N	146,207	129,444	90,172	146,201	129,452	90,172	148,415
Adj. R^2	0.800	0.071	0.030	0.800	0.066	0.027	0.148
Time FE	Y	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y	Y

Table 7: Fund Performance and Evaluation Horizon II This table presents OLS regression results where the dependent variables are (1) buy-and-hold fund return over the next 1 year starting from month t (BHR_{1y}); (2) buy-and-hold fund return over the next 3 years starting from month t (BHR_{3y}); (3) buy-and-hold fund return over the next 5 years starting from month t (BHR_{5y}); (4) BHR_{1y} minus buy-and-hold returns to the benchmark over the next 1 year starting from month t ($BHAR_{1y}$); (5) BHR_{3y} minus buy-and-hold returns to the benchmark over the next 3 years starting from month t ($BHAR_{3y}$); (6) BHR_{5y} minus buy-and-hold returns to the benchmark over the next 5 years starting from month t ($BHAR_{5y}$). The key independent variable of interest is 'Long horizon', which takes the value of 1 if the evaluation horizon used to determine the manager's performance bonus pay is longer than one year, and 0 otherwise. The control variables are the natural logarithm of the fund's NAV (in $Billion), the natural logarithm of fund age (in years), fund turnover ration, fund expense ration, and fund flow. The explanatory variables are lagged by one month relative to the dependent variable. Variable definitions are offered in Table A.1 in the Appendix. We control for time and fund style fixed effects, and cluster standard errors by time and fund. Reported in parentheses are t-statistics. $***$, $**$, and $*$ indicate statistically significance at the 1%, 5%, and 10% level, respectively.

	(1) BHR_{1y}	(2) BHR_{3y}	(3) BHR_{5y}	(4) $BHAR_{1y}$	(5) $BHAR_{3y}$	(6) $BHAR_{5y}$
Long horizon (t-1)	0.669^{***}	2.143^{***}	4.047^{***}	0.642^{***}	2.201^{***}	4.209^{***}
	(5.305)	(5.160)	(4.657)	(5.238)	(5.347)	(4.937)
lnAssetsB (t-1)				0.058	0.096	0.074
				(1.319)	(0.648)	(0.258)
lnAge (t-1)				0.144^{*}	-0.098	-0.538
				(1.700)	(-0.343)	(-0.887)
Turnover ratio (t-1)				-0.590^{***}	-1.601^{***}	-1.967^{**}
				(-3.505)	(-3.637)	(-2.079)
Exp ratio (t-1)				0.238	0.405	-0.258
				(0.986)	(0.554)	(-0.183)
Flow (t-1,t)				-0.078	-2.813^{**}	-10.305^{***}
				(-0.151)	(-2.088)	(-3.673)
Constant	-0.212^{**}	-1.128^{***}	-1.059	-0.305	0.348	3.656
	(-2.162)	(-3.439)	(-1.549)	(-0.937)	(0.327)	(1.612)
N	134,119	110,387	78,753	129,555	106,596	75,873
Adj. R^2	0.07	0.058	0.064	0.079	0.069	0.071
Time FE	Y	Y	Y	Y	Y	Y
Style FE	Y	Y	Y	Y	Y	Y

Table 8: Family Characteristics of Long- and Short-Horizon Funds For each fund, 'Long Horizon' (LH) is a dummy takes the value of 1 if the evaluation horizon used to determine the manager's performance bonus pay is longer than one year, and 0 otherwise. We define a fund family to be long horizon if the value weighted average of its funds' 'Long Horizon' (LH) is at least 0.5, or short horizon family otherwise. The variables - fund age, defined contribution (DC) asset ratio, expense ratio, flow-performance sensitivity (FPS), turnover ratio - are value weighted each month across all funds within the family; the weights are the funds' TNA in the prior month. DC asset ratio is missing for many funds. We code the family-level DC asset ratio as missing if this variable is missing for more than 50% of the funds in the family. The variable TNA is the aggregated TNA of all funds in the family. The unit of observation is family-month. Variable definitions are offered in Table A.1 in the Appendix. Standard errors are clustered by family and by time. $***$, $**$, and $*$ indicate statistically significance at the 1%, 5%, and 10% level, respectively.

	Long-Horizon Family	Short-Horizon Family	Long - Short
Fund age	14.897	13.167	1.730^{***}
DC ratio	0.247	0.235	0.012
Expense ratio	1.067	1.259	-0.192^{***}
FPS	0.548	0.784	-0.236^{**}
TNA ($million)	7,512.27	2,854.17	$4,658.098^{***}$
Turnover ratio	67.514	77.960	-10.446^{**}

Table 9: Determinants of Long-Horizon Evaluation Contracts This table presents OLS regression results where the dependent variable is a dummy variable that takes the value of 1 if the fund's manager evaluation horizon is longer than 1 year, and 0 otherwise. The explanatory variables of interest are: fund flow-performance sensitivity (FPS), the fraction of defined contribution (DC) assets in the portfolio, and ILP_LC, which a binary variable that takes the value of 1 if an inter-fund lending program or lines of credit is available from the fund family, or 0 otherwise. The control variables are the natural logarithm of the fund's NAV (in $Billion), the natural logarithm of fund age (in years), fund turnover ration, fund expense ration, fund flow, and the number of funds in the family. The explanatory variables are lagged by one month relative to the dependent variable. Variable definitions are offered in Table A.1 in the Appendix. The sample in the last column is limited to 2018 due to limited availability of the variable ILP_LC. We control for time and fund style fixed effects, and cluster standard errors by time and fund. Reported in parentheses are t-statistics. $***$, $**$, and $*$ indicate statistically significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
FPS	-0.0053**		-0.0039*		
	(-2.3135)		(-1.6889)		
DC ratio		0.3178***		0.1993*	
		(2.6381)		(1.6696)	
lnAssetsB (t-1)			0.0547***	0.0507***	
			(4.0417)	(3.7552)	
lnAge (t-1)			0.0117	0.0173	
			(0.3573)	(0.5285)	
Turnover ratio (t-1)			0.0906***	0.0857***	
			(2.8606)	(2.7032)	
Exp ratio (t-1)			0.0112	0.0171	
			(0.1676)	(0.2618)	
Flow (t,t-1)			-0.0050*	-0.0043	
			(-1.6660)	(-1.4214)	
#funds_family (t-1)			0.0010	0.0010	
			(1.1326)	(1.2019)	
ILP_LC					0.2571***
					(3.991)
Constant	0.7015***	0.6335***	0.5728***	0.5121***	0.3134***
	(34.6023)	(18.3071)	(4.7022)	(4.1008)	(6.510)
Observations	33,433	33,433	31,452	31,452	670
R-squared	0.0164	0.0255	0.0588	0.0620	0.0671
Time FE	Yes	Yes	Yes	Yes	No
Style FE	Yes	Yes	Yes	Yes	No
Cluster SE	Fund and Time	Fund and Time	Fund and Time	Fund and Time	Family

APPENDIX

Contract Evaluation Horizon and Fund Performance

April 23, 2024

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.

Table A.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
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
# stocks	The number of stocks in the fund's portfolio. When portfolio holdings are unavailable, we supplement it with the number of stocks reported in MFLINKS2.
Top10 hvalue	Percentage of aggregate dollar value of the top 10 holdings
Active share	Percentage of fund portfolio deviation from its benchmark portfolio as defined in Cremers and Petajisto (2009)
FPS	Flow-performance sensitivity of a fund. It is estimated by regressing flows on to the monthly returns using the 24 month rolling windows. To reduce noises, the monthly returns are calculated as the average monthly returns over the past 12 months. See Mariaseuntta and Kahraman (2017) for more details
ILP LC	A binary variable that takes the value of 1 if the fund arranges interfund lending programs or lines of credits during that year, or 0 otherwise.
Clientele	
DC ratio	Percentage of assets provided through defined contribution plans
Monthly returns	
Total return	The gross return of the fund in percentage
Net return	The fund return in percentage net of expense ratio
Excess net return	The fund return in 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 net 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
Buy-Hold returns	
BHAR n	Buy-and-hold gross return net of buy-and-hold return of benchmark over the next n months where $n = 12, 24, 36, 48$

Table A.2: Fund Performance and Evaluation Horizon - Matched Sample In this table, we re-estimate Panel B of 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.3: 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 A.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.4: Robustness Test II. Manager Turnovers. The dependent variable is *to_evalhorizon* which captures the manager's evaluation horizon at the new fund. This variable takes the value of 1, 3, 5, or 10 years. We include multiple explanatory variables that characterize either the managers or the funds. For the manager characteristics, we include Mgr. Benchmark Adj. Ret 36 (or Mgr. Benchmark Adj. Ret 60) indicating the benchmark adjusted returns of the manager at the previous fund over the past 36 (or 60) months. These are value weighted among all the funds managed by the manager in given a month. Also included are the fund characteristics: *From_evalhorizon* refers to the evaluation horizon of the departing fund. *From_num. comgrs* refers the number of managers in the departing fund. *From_assets* indicates the assets under management of the departing fund. Standard errors are clustered by fund and by time.

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mgr. Bk. Adj. Ret 36	0.503***		0.251**		0.361***		0.535***	
	(3.877)		(2.002)		(2.594)		(2.811)	
Mgr. Bk. Adj. Ret 60		0.963***		0.328*		0.198		0.383
		(5.025)		(1.792)		(0.695)		(1.085)
From_evalHorizon			0.474***	0.446***	0.278***	0.215***	−0.025	−0.022
			(24.137)	(19.693)	(4.614)	(2.783)	(-0.990)	(-0.764)
From_num. comgrs			−0.005	−0.012	−0.024	−0.034	−0.007	−0.007
			(-0.785)	(-1.528)	(-1.373)	(-1.635)	(-1.095)	(-0.909)
From_assetsB			0.030***	0.033***	0.050***	0.032	0.004	0.005
			(7.755)	(6.829)	(3.487)	(1.385)	(0.589)	(0.622)
Constant	4.007***	4.007***	2.051***	2.160***	2.899***	3.221***	4.180***	4.150***
	(129.892)	(109.183)	(21.937)	(19.997)	(11.245)	(9.539)	(36.410)	(31.309)
N of obs	2,208	1,678	1,874	1,456	1,677	1,259	1,671	1,298
Adj. R^2	0.192	0.189	0.424	0.402	0.653	0.612	0.759	0.735
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE					Y	Y		
Manager FE							Y	Y

Table A.5: Fund Performance, Evaluation Horizon, and Fund Holding Horizon In this table, we reproduce Panel B of 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 (2023). 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)	0.075***	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

A.1 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.