The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXXIX, NO. 3 • JUNE 2024

A Horizon-Based Decomposition of Mutual Fund Value Added Using Transactions

JULES VAN BINSBERGEN, JUNGSUK HAN, HONGXUN RUAN, and RAN XING*

ABSTRACT

We decompose mutual fund value added by the length of funds' holdings using transaction-level data. We motivate our decomposition with a model featuring horizon-specific investment ideas, where short-term ideas are less scalable because the associated trades cannot be spread over time. Fund turnover correlates negatively with the horizon over which value is added and positively with price impact costs. As predicted, holdings of high-turnover funds add a substantial amount of value in the first two weeks, of which more than 80% is earned on Federal Open Market Committee (FOMC) and earnings announcement days. Holdings of low-turnover funds add value only over longer horizons.

THE OBJECTIVE OF ACTIVE MUTUAL funds is to find investments that add value over and above their investors' alternative investment opportunity set. How funds achieve this objective exhibits large cross-sectional variation in the data, particularly when it comes to the average holding period of such investments. For example, the BlackRock Mid-Cap Growth Fund changes its portfolio once every two to three years, while the Berkshire Focus Fund changes its portfolio about 10 times per year.[1] Important questions that arise are whether high-turnover mutual funds are skilled at identifying short-term investment

*Jules van Binsbergen is at The Wharton School. Jungsuk Han is at Seoul National University. Hongxun Ruan is at Peking University, Guanghua School of Management. Ran Xing is at Stockholm University and Aarhus University. Authors are listed in alphabetical order. We are grateful for comments from our discussants, Richard Evans, Francesco Franzoni, Nataliya Gerasimova, Markus Ibert, Yuehua Tang, and Min Zhu. We are also grateful for comments from Joost Driessen; Frank de Jong; Mancy Luo; Russell Jame; Esad Smajlbegovic; conference participants at Western Finance Association Conference, Financial Intermediation Research Society Conference, the Finance Down Under Conference, China International Conference in Finance, the Young Scholars Nordic Finance Workshop; and seminar participants at Virtual Asset Management Seminar Series, Erasmus University Rotterdam, Tilburg University, Aarhus University, and Stockholm University. We thank Yuehua Tang for sharing the method to identify mutual funds in the Ancerno database. Xing gratefully acknowledges the financial support provided by the Swedish House of Finance (SHoF). Han gratefully acknowledges the financial support provided by the Institute for Management Research at Seoul National University. We have read *The Journal of Finance* disclosure policy and have no conflicts of interest to disclose

Correspondence: Ran Xing, Stockholm University, Företagsekonomiska institutionen, 106 91 Stockholm, Sweden; e-mail: ran.xing@sbs.su.se.

[1] These values are based on Morningstar data as of September 18, 2020.

DOI: 10.1111/jofi.13331

opportunities, and if so, how high price impact costs affect their short-term investment choices. These questions remain open in the mutual fund literature mainly because of the anonymity of transaction-level data.[2] In this study, we decompose funds' value added (Berk and van Binsbergen (2015)) based on this past length of their holdings using transaction-level data. We find that holdings of high-turnover funds add a substantial amount of value in the first two weeks after accounting for the price impact costs of trades. More than 80% of this value is added on Federal Open Market Committee (FOMC) and earnings announcement days. Holdings of low-turnover funds add value only over longer horizons.

While our paper is largely empirical, we use an extension of the Berk and Green (2004) model to motivate our empirical analysis and sharply define the null hypotheses considered. We deviate from Berk and Green (2004) in two important respects. First, our model features funds that specialize in identifying investment opportunities at different investment horizons. A fund chooses its investment horizon (fund turnover) based on its horizon-specific skill, optimally taking into account the associated price impact costs. Second, unlike Berk and Green (2004), our model features endogenous heterogeneity in decreasing returns to scale across investment horizons by incorporating a fund's trading process under price impact costs (analogous to Kyle (1985)).[3] Our main intuition is as follows. Funds investing in short-term opportunities cannot spread their trades over time to the same extent as funds investing in long-term opportunities can, which implies that price impact costs are higher for the former group. A fund optimally chooses to invest in short-term opportunities if the present value of doing so exceeds that of investing in long-term opportunities, and vice versa. This present value depends on (i) the gross alpha before price impact costs are taken into account, (ii) the price impact costs or scalability of the strategy, and (iii) the fact that multiple short-term investments can be deployed in the same time span as one long-term investment. Our model illustrates that value added, which accounts for the horizon-specific decreasing returns to scale, is a more appropriate skill measure than (gross and net) alpha. The model also provides empirically testable predictions of the correlation between fund turnover and the horizon over which value is added, as well

[2] Influential papers that have made progress on this dimension are Keim (1999) and Frazzini, Israel, and Moskowitz (2012), who obtain transaction data from a single fund management firm, the former from Dimensional Fund Advisors (DFA) and the latter from AQR Capital Management. Di Mascio, Lines, and Naik (2017) and von Beschwitz, Lunghi, and Schmidt (2022) obtain transaction-level data for pension funds and hedge funds from Inalytics Ltd. Puckett and Yan (2011), Jame (2018), and Çötelioğlu, Franzoni, and Plazzi (2021) use Ancerno data (the data we use) to identify a subset of institutional investors using a list of fund-managing firms. Busse et al. (2021) identify a subset of mutual funds by matching their transactions in Ancerno with quarterly holdings.

[3] Berk and Green (2004) assume the same decreasing returns-to-scale parameter for all funds. For more studies exploring the importance of decreasing returns to scale at the fund level, see Chen et al. (2004), Edelen, Evans, and Kadlec (2007), Pollet and Wilson (2008), Yan (2008), Berk and van Binsbergen (2015), Pástor, Stambaugh, and Taylor (2020), and Barras, Gagliardini, and Scaillet (2022).

as their correlations with price impact costs. Specifically, our model predicts that high-turnover funds add more value through their short-term holdings and low-turnover funds add more value through their long-term holdings.

It is worth clarifying that the trade-off between alpha and price impact costs in our model applies to known characteristics-based trading strategies (e.g., momentum and value) as well as alpha-generating strategies unrelated to these known factors. In this paper, we define a fund's skill as the ability to implement a strategy at a cost lower than its profit, using the Capital Asset Pricing Model (CAPM) as the benchmark model and value added after price impact costs as the measure of skill.[4]

To test our model's predictions, we need to calculate the value added from both long- and short-term holdings. This requires examining holdings within a quarter. To this end, we merge the transaction data provided by Abel Noser Solutions (known as Ancerno data) with the quarterly holdings data in the Thomson Reuters database from 1999 to 2010 (using the method in Busse et al. (2021)) and the mutual fund data (including fund characteristics) from the Center for Research in Security Prices (CRSP). Using these data, we identify 331 U.S. mutual funds and construct a unique data set of their daily holdings. We decompose a fund's daily holdings into short- and long-term holdings (holdings shorter and longer than n days), and we compute the fund's daily value added from each separately. This analysis using daily holdings and transactions sets us apart from previous studies that only use quarterly holdings data and thus cannot compute the short-term effects of trading (and the associated price impact) on funds' value added and performance.

As predicted by the model, our decomposition based on transactions shows markedly different results depending on fund turnover: for high-turnover funds, the holdings (net purchases) shorter than two weeks add a substantial amount of value, whereas for low-turnover funds, such holdings do not add value. Conversely, for low-turnover funds, the holdings longer than a year add the majority of value, whereas such holdings do not add value for high-turnover funds. These results are consistent with the existence of horizon-specific investment skills. We formally test the model's prediction that there is a positive (negative) correlation between turnover and short-term (long-term) value added using standard regression analysis as well as order statistics. Consistent with this logic, we find that the source of value added is different between high- and low-turnover funds. That is, more than 80% of high-turnover funds' short-term value added within two weeks is earned on FOMC and earnings announcement days, while exposure to the value factor explains the majority of low-turnover funds' long-term value added. Exposure to the momentum factor also explains part of high-turnover funds' short-term value added.

[4] As documented in Patton and Weller (2020), mutual funds on average earn low returns to value and no returns to momentum after accounting for implementation costs. Value and momentum factors in the Fama-French three-factor model (FF3) and the Fama-French-Carhart four-factor model (FFC4) do not account for the price impact costs of trades. Therefore, using either of these two models as a benchmark underestimates the value added of a fund.

Our model also predicts a positive correlation between fund turnover and price impact costs, controlling for fund size because it is more difficult to spread trades over time when engaging in short-term investing. To test this prediction, we double-sort funds into 25 portfolios based on both their turnover and size, and calculate the average price impact costs as measured by the execution shortfall of trades for each portfolio. This double-sorting analysis confirms the predicted positive correlation between fund turnover and price impact costs. While high-turnover funds in all size quintiles consistently pay a large amount of price impact costs, low-turnover funds profit from providing liquidity during the execution of their trades. Standard regression analysis further shows that fund turnover is an important determinant of price impact costs among all fund-level characteristics.

We compare the alphas of high- and low-turnover funds' net purchases before price impact costs, showing that the alpha captured by high-turnover funds shortly after their trades is substantially larger than that captured by low-turnover funds. This result supports the idea that high- and low-turnover funds profit from different alpha opportunities, instead of trading for the same opportunity at different frequencies. When calculating stock alphas (before price impact costs), we use the execution shortfall of trades as an independent measure of price impact costs. This approach differs from the literature on decreasing returns to scale, which simply models the erosion of alpha as a linear function of fund size (e.g., Zhu (2018) and Barras, Gagliardini, and Scaillet (2022)).[5]

We further uncover the determinants of the decreasing returns-to-scale parameters of funds using transaction data and requantify the importance of spreading trades over time relative to other determinants of decreasing returns to scale in the literature including stock liquidity, number of investment ideas (e.g., Harvey et al. (2021)), and trade execution skill (e.g., Anand et al. (2012)). Evidence in our paper suggests that the flexibility to spread trades over time is the most important determinant of funds' decreasing returns to scale across fund turnover quintiles, which explains why the scalability of high-turnover funds is *lower* than that of low-turnover funds as documented in Barras, Gagliardini, and Scaillet (2022). Moreover, we document that the scalablity of high-turnover funds is *higher* than that of low-turnover funds *after controlling for the spreading of trades over time*, which we attribute to high-turnover funds' larger number of short-term investment ideas, as opposed to better trade execution skill or more liquid stock holdings. The larger number, together with the higher alphas, of high-turnover funds' short-term investment opportunities suggests that funds account for both the scale and quality of their investment ideas when choosing between short- and long-term investing.

[5] Barras, Gagliardini, and Scaillet (2022) also use a log function and a fully flexible function to address this concern about misspecification. Berk and van Binsbergen (2015, 2017) use the value-added measure, which does not need any parametric assumption on the fund-specific relationship (decreasing returns to scale) between gross alpha and size. Value added (the product of size and gross alpha) simply measures the end result in dollars.

In our final set of tests, we show that our findings can be generalized to a larger sample of mutual funds using the monthly holdings data of 2,492 U.S. equity funds from 1993 to 2020. The results are somewhat weaker because monthly holdings neglect all intraday trading profits and profits realized before the end of a month. Moreover, without transaction and daily holdings data, the price impact costs of trades and short-term trading profits within a month cannot be estimated.

Our study relates to Cremers and Pareek (2016) and Lan, Moneta, and Wermers (2023), who use fund returns and quarterly holdings data to investigate the long-term stock-picking skill of low-turnover funds. They document that low-turnover (long-duration/horizon) funds outperform their benchmarks before expenses, whereas high-turnover (short-duration/horizon) funds do not. This evidence is more consistent with the notion of high-turnover funds trading too much, destroying value in the process, rather than funds specializing at different investment horizons. They provide evidence supporting low-turnover funds having stock selection skill at longer horizons using quarterly holdings, but provide no evidence on high-turnover funds *lacking* skill identifying short-term opportunities. In contrast, using transaction-level data and value added to measure skill, we document that high-turnover funds do possess short-term stock selection skills, supporting the premise of our paper that funds specialize at different investment horizons. The analysis of price impact costs further shows that funds trade off the magnitude of alpha against the price impact costs of trades when choosing between short- and long-term opportunities.

Our study also relates to a literature that highlights the importance of specialization in the mutual fund industry. Van Nieuwerburgh and Veldkamp (2009) argue that once a fund starts to acquire information about a stock, country, or industry, it is likely to continue this investment in information acquisition and build up its comparative advantage in that area. Crouzet, Dew-Becker, and Nathanson (2020) further show that investors build horizon-specific skills endogenously for similar reasons. These papers thus provide an important motivation for our infinite-horizon trading model with horizon-specific skill and price impact costs. While skills are difficult to observe, fund turnover is directly observable. Since a fund chooses its turnover endogenously according to its skills (potential value added) at different horizons, fund turnover contains information about its horizon-specific skills.

A large empirical literature investigates the relations between fund size, price impact costs, and fund performance (e.g., Edelen, Evans, and Kadlec (2007), Pollet and Wilson (2008), Yan (2008), Pástor, Stambaugh, and Taylor (2020), and Busse et al. (2021)).[6] The results of this literature are mixed, which is consistent with our model's prediction that the pairwise correlations between fund size, price impact costs, and fund gross alpha are ambiguous in sign (before controlling for fund turnover). Pástor, Stambaugh, and Taylor

[6] Also refer to the large corpus of literature on decreasing returns to scale at the fund-level, including Berk and Green (2004), Chen et al. (2004), Zhu (2018), and Barras, Gagliardini, and Scaillet (2022).

(2020) extend the Berk and Green model by assuming a functional form of trading costs that depends not only on fund size but also on other fund characteristics such as fund turnover and portfolio liquidity. While they incorporate fund turnover into their model as an exogenously given characteristic, we endogenize fund turnover by solving an optimal investment problem with horizon-specific skills under price impact costs. Our transaction-level data enable us to empirically measure funds' short-term alpha opportunities and price impact costs. Furthermore, our dynamic model allows optimal spreading of trades over time as in Kyle (1985), and we empirically identify the flexibility to spread trades as the most important determinant of funds' decreasing returns to scale across fund turnover quintiles.

Our decomposition approach contributes to the current methods available for the analysis of fund performance by investment horizons and the analysis of investors' trading skill. Most existing analyses assume one horizon for all of the trades of each fund.[7] Cremers and Pareek (2016) and Lan, Moneta, and Wermers (2023) construct direct measures for the average investment horizon of a fund. However, different trades of one fund usually target profits at different horizons.[8] Different from these studies, we focus on a fund's value added over different investment horizons and the specific trade-offs it faces when choosing between short- and long-term investment opportunities; our decomposition method allows for different horizons for different holdings of the same fund. For the analysis of investors' trading skill, a common practice in the literature is to separately aggregate all purchases and sales and then investigate whether trades can predict future stock returns in a fixed time period shortly after.[9] However, our model and decomposition method emphasize the importance of keeping track of funds' actual holdings after their trades (since funds may have sold those stocks in the meantime) and accounting for both short- and long-term trading performance in a unified framework. Funds may sacrifice their short-term trading profits for better long-term performance as in our model.

Recently, there has been an increased focus in the mutual fund literature on holdings and transactions. On the one hand, a large thread of literature uses quarterly holdings data to explore, using alpha measures, whether or which fund managers outperform.[10] Although quarterly holdings are useful, they are only infrequent snapshots of funds' portfolios and neglect the short-term effect

[7] Studies using fund turnover and churn ratio as measures of the average investment horizon of a fund include Bushee (1998, 2000, 2001), Gaspar, Massa, and Matos (2005), Yan and Zhang (2009), Cella, Ellul, and Giannetti (2013), and Pástor, Stambaugh, and Taylor (2017). Most studies use quarterly holdings data to construct their horizon measures.

[8] As Di Mascio, Lines, and Naik (2017) document, there is large dispersion in the investment horizons of trades for the same fund.

[9] See, for example, Chen, Jegadeesh, and Wermers (2000), Yan and Zhang (2009), Puckett and Yan (2011), Chakrabarty, Moulton, and Trzcinka (2017), and Busse et al. (2021).

[10] This thread of literature includes Daniel et al. (1997), Wermers (2000), Kacperczyk, Sialm, and Zheng (2005), Cohen, Coval, and Pástor (2005), Cremers and Petajisto (2009), Da, Gao, and Jagannathan (2011), Dong and Massa (2013), Cremers and Pareek (2015), Kacperczyk, Nieuwerburgh, and Veldkamp (2014, 2016), and Dong, Feng, and Sadka (2019). Another thread uses the

of trades on fund performance. To capture this short-term effect, Kacperczyk, Sialm, and Zheng (2008) measure the impact of intraquarter trades on performance through the return gap (the gap between the reported fund return and the return implied by quarterly holdings). The existence of this return gap suggests that higher-frequency observations of funds' trades can be informative about the sources of fund manager skill. On the other hand, a growing body of literature uses transaction-level data of institutional investors to study fund skill, finding mixed results.[11] Because of the anonymity of institutional investors, these articles cannot link their analyses to long-term holdings and compare the contribution of trades across different horizons. In this study, we close this gap by merging transaction data with quarterly holdings data and designing a method to measure all of the open positions' impact on a fund's value added by the past length of holding periods.

Our study also relates to the trading cost literature, which estimates trading costs from transaction data (e.g., Chan and Lakonishok (1997), Keim and Madhavan (1996, 1997), Bikker, Spierdijk, and van der Sluis (2007), and Briere et al. (2019)). Moreover, the liquidity provision of low-turnover funds documented in this study complements studies investigating the relationship between the liquidity provision of trades, fund performance, and stock liquidity (e.g., Keim (1999), Jame (2018), and Çötelioğlu, Franzoni, and Plazzi (2021)).

The rest of the paper proceeds as follows. Section I introduces a motivating model for our analysis. Section II explains the method used to decompose fund value added by investment horizon. Section III presents summary statistics for our sample of mutual funds and the measures used for trading costs. In Section IV, we conduct empirical analyses on fund value added, alphas, price impact costs, and decreasing returns to scale. Section V concludes.

I. Theoretical Motivation

In this section, we build a stylized dynamic trading model featuring price impact where a mutual fund can choose investment opportunities with different horizons given its horizon-specific skills. The fund manager is compensated by active trading gains in excess of the passive benchmark.

aggregate quarterly holdings (or changes in quarterly holdings) of a group of skilled funds to predict stock returns, including Chen, Jegadeesh, and Wermers (2000), Alexander, Cici, and Gibson (2007), Pool, Stoffman, and Yonker (2012, 2015), Wermers, Yao, and Zhao (2012), and Lan, Moneta, and Wermers (2023).

[11] For example, Campbell, Ramadorai, and Schwartz (2009) infer daily institutional trades from the Transactions and Quotes (TAQ) database and 13F filings and find that institutional trades generate short-term losses but longer-term profits. Puckett and Yan (2011) find that institutional investors earn significant abnormal returns on their trades intraquarter and that interim trading skill is persistent. Jame (2018) documents that hedge funds that provide liquidity outperform, and Busse et al. (2019) find that institutional investors that trade regularly profit more from their trades. In contrast, Chakrabarty, Moulton, and Trzcinka (2017) document that a majority of short-term institutional round-trip trades lose money and find no evidence of persistent outperformance in short-term institutional trades.

There are two types of investment opportunities—short-term and long-term investment opportunities, which are denoted by S and L, respectively. An investment opportunity $h \in \{S, L\}$ pays a risk-adjusted return of $R_h = \alpha_h + \epsilon_h$ against the benchmark return at the end of its investment horizon T_h, where α_h is a positive constant and ϵ_h is an independently and identically distributed random variable with mean zero. The short-term opportunity S has a shorter horizon than the long-term opportunity L, that is, $T_S < T_L$. We assume that in each period t, the fund trades at the beginning of the period, and the payoff may realize at the end of the period. Upon the payoff of the existing investment opportunity, the fund (i) finds new short-term and long-term investment opportunities, (ii) chooses either of the two opportunities,[12] and (iii) chooses the amount of capital, q_h, to invest in this opportunity and reallocates capital from the old investment to the new one.[13] Our model captures the idea of funds' horizon-specific skills by α_S and α_L, which are the mean risk-adjusted returns against the benchmark in the short horizon and in the long horizon, respectively.

The price impact costs of changing positions in the dollar amount of w_t from an existing investment to a new investment are given by a quadratic function,

$$C(w_t) = \frac{\lambda}{2} w_t^2, \tag{1}$$

where λ is a positive constant.[14] This is equivalent to a linear relation between the trading amount and the price impact costs expressed as a percentage. The quadratic cost function is assumed for ease of exposition, and our results are not affected qualitatively by the alternative assumption of a general convex cost function. We further assume that short sales are not allowed, that is, $w_t \geq 0$.

The fund has a discount factor of $\beta \in (0, 1)$. Given the opportunity $h \in \{S, L\}$ and the amount of capital to invest in this opportunity q_h, the fund's value is the sum of the present values of trading gains $E[R_h]q_h$ and the continuation

[12] Since we focus on the fund's specialization at different investment opportunities in this study, we do not allow the fund to invest in multiple opportunities at the same time. That said, allowing the fund to invest in multiple opportunities at the same time does not affect the main message of our model. The only difference is in the optimal portfolio weights: instead of choosing the opportunity that the fund specializes in, the fund tilts its portfolio weights toward the opportunities it is specialized in.

[13] Later we show that, in the framework of Berk and Green (2004) and Berk and van Binsbergen (2015, 2017), the optimal amount of capital invested in the opportunity, q_h, depends on the opportunity h, and it is fixed over time if the fund's skill is fixed over time.

[14] The parameter λ may differ across stocks and portfolios in terms of liquidity (e.g., Zhu (2018), Pástor, Stambaugh, and Taylor (2020)), and across funds in terms of trade execution skill (e.g., Anand et al. (2012) and Frazzini, Israel, and Moskowitz (2012)) or the number of investment ideas (e.g., Harvey et al. (2021)). Busse et al. (2021) show that fund turnover remains a significant determinant of price impact costs after controlling for these characteristics at both the fund level and the transaction level. In this paper, we focus on the heterogeneity of decreasing returns to scale related to the investment horizon while abstracting from other sources of heterogeneity.

value J less price impact costs $C(w_\tau)$,

$$J_h = \max_{(w_1, w_2, \ldots, w_{T_h}) \in \mathcal{W}} - \sum_{\tau=1}^{T_h} \beta^{\tau-1} C(w_\tau) + \beta^{T_h - 1}\big(E[R_h] q_h + \beta J\big), \tag{2}$$

where $\mathcal{W}$ is the set of feasible investment allocations,

$$\mathcal{W} \equiv \left\{ \big(w_1, w_2, \ldots, w_{T_h}\big) \in \mathbb{R}_+^{T_h} \,\middle|\, \sum_{\tau=1}^{T_h} w_\tau = q_h \right\}, \tag{3}$$

and J is the continuation value of the fund upon the realization of the final payoff of the existing investment opportunity,

$$J \equiv \max(J_S, J_L), \tag{4}$$

which is the value of choosing either a new short-term or a new long-term opportunity.

We derive the fund's optimal trading policy of investing capital q_h in the chosen investment opportunity h, in which the fund splits its trades over time to minimize price impact costs.

LEMMA 1: *Given the amount of capital q_h, the optimal solution for the trading problem of investment opportunity h is given by*

$$w_\tau^* = \beta^{-(\tau-1)} \frac{q_h}{\Gamma_h}, \text{ for all } \tau = 1, \ldots, T_h, \tag{5}$$

and the present value of price impact costs is given by

$$\sum_{\tau=1}^{T_h} \beta^{\tau-1} C(w_\tau^*) = \frac{\lambda q_h^2}{2\Gamma_h}, \tag{6}$$

where

$$\Gamma_h \equiv \sum_{\tau=1}^{T_h} \beta^{-(\tau-1)}.$$

PROOF: See the Appendix. □

To see the intuition of Lemma 1 more clearly, consider the limiting case in which there is no discounting (i.e., $\beta \to 1$). Then, equation (5) implies that the fund trades an equal amount every period, that is, $w_\tau^* = q_h / T_h$. This is in line with standard trading models with price impact in the literature such as Kyle (1985). This intuition extends to the situation in which there is randomness in the mispricing wedge and its duration (e.g., Back and Baruch (2004), Caldentey and Stacchetti (2010), Gârleanu and Pedersen (2013)). For example, Gârleanu and Pedersen (2013) further show that, under transaction costs and stochastically decaying alpha, the mean variance optimal portfolio gradually approaches the target.

We denote the present value of the fund's total value added given the strategy of repeatedly choosing investment opportunity h by $\hat{J}_h$. Then substituting equation (6) into equation (2) yields

$$\hat{J}_h = -\frac{\lambda q_h^2}{2\Gamma_h} + \beta^{T_h - 1}\Big(\alpha_h q_h + \beta \hat{J}_h\Big). \tag{7}$$

It is important to note that the present value of the fund $\hat{J}_h$ reflects the fact that the fund investing in the short-term opportunity can deploy its capital more often in new investment opportunities whereas the fund investing in the long-term opportunity can do so less often.[15] That is, solving equation (7) for $\hat{J}_h$ gives

$$\hat{J}_h = a_h q_h - b_h q_h^2, \tag{8}$$

where a_h captures the compounding alpha from reinvesting in new opportunities in the future at a frequency associated with opportunity h,

$$a_h \equiv \left(\frac{\beta^{T_h}}{1 - \beta^{T_h}}\right)\alpha_h, \tag{9}$$

and b_h captures the compounding costs

$$b_h \equiv \frac{\lambda}{2(1 - \beta^{T_h})\Gamma_h}. \tag{10}$$

The first term of equation (8) is the present value of trading gains and the second term is the present value of price impact costs, given the capital for investing q_h and the fund's alpha opportunity α_h for each strategy h, respectively. The following result on endogenous differences in price impact costs across investment horizons is immediate from equation (10).

COROLLARY 1: *Under the optimal trading policy given in Lemma 1, price impact costs are larger for the short-term opportunity than the long-term opportunity per unit of investment, that is,*

$$b_S > b_L. \tag{11}$$

Dividing equation (8) by q_h gives the gross alpha (the alpha before fees but after price impact costs) of a fund that chooses strategy h and invests all of its capital in this strategy

$$\alpha^g(q_h) \equiv \frac{\hat{J}_h}{q_h} = a_h - b_h q_h. \tag{12}$$

Our expressions for value added in equation (8) and gross alpha in equation (12) are closely related to those of gross alpha (Berk and Green (2004)) and

[15] See, for example, Dow, Han, and Sangiorgi (2021) for further discussions.

one-period value added ((Berk and van Binsbergen (2015, 2017)), though we incorporate horizon-specific skills (value added) and costs in a dynamic setting.

Using the optimal trading policy obtained in Lemma 1, which minimizes price impact costs, the optimal size of actively managed capital q_h^* can be derived from the first-order condition of maximizing $\hat{J}_h$. By setting the first-order derivative of equation (8) with respect to q_h equal to zero, we obtain

$$q_h^* = \frac{a_h}{2b_h}, \tag{13}$$

which implies that the optimal fund size q_h^* depends on both the portfolio alpha before price impact costs a_h and the price impact costs b_h.

We now endogenize fund flow by assuming that investors have rational expectations, as in Berk and Green (2004). Rational investors chase any investment opportunity with a positive net present value, which implies that all funds must have a net alpha of zero in equilibrium:

$$\alpha^n(q_h) \equiv \alpha^g(q_h) - f = 0. \tag{14}$$

Using equations (12) to (14), we find that choosing the level of fee $f^* = a_h/2$ induces the optimal size of actively managed capital in equation (13).[16] Therefore, substituting equation (13) into equation (8) gives the maximum present value of value added when the fund chooses strategy h,

$$\hat{J}_h^* = \frac{a_h^2}{4b_h} = \frac{a_h^2}{2\lambda}(1-\beta^{T_h})\Gamma_h, \tag{15}$$

where the second equality is due to equation (10). Equation (15) indicates that the maximum present value of value added $\hat{J}_h^*$ correlates positively with fund size q_h^*, since substituting equation (13) and $f^* = a_h/2$ into equation (15) gives

$$\hat{J}_h^* = q_h^* f^*. \tag{16}$$

Using the stationarity of the optimal choice problem between S and L, the following proposition states that if the fund optimally chooses one opportunity over the other once, it always does.

PROPOSITION 1: *The fund chooses the short-term opportunity if and only if the present value of investing in the short-term opportunity is higher than the present value of investing in the long-term opportunity,*

$$\hat{J}_S^* = \frac{a_S^2}{4b_S} > \frac{a_L^2}{4b_L} = \hat{J}_L^*. \tag{17}$$

PROOF: See the Appendix. □

[16] See the Appendix for the generalization with passive indexing, in which case it is optimal for the fund to choose any fee less than or equal to f^* to raise enough capital for investing in opportunity h. Then, the optimal strategy is to put q_h^* into active management and index the rest. Passive indexing does not change our results otherwise.

Proposition 1 shows that the fund always chooses the opportunity that gives the largest present value. The choice between short- and long-term investment opportunities depends not only on the fund's alpha opportunity at each investment horizon a_h, but also on the average price impact costs of investing in each investment horizon b_h, which is smaller for longer horizons as shown in Corollary 1.

PROPOSITION 2: *The present value of equilibrium price impact costs as a percentage of total trading amounts can be represented as a function of the fund's alpha opportunity, that is,*

$$PI_h = b_h q_h^* = \frac{a_h}{2}. \tag{18}$$

PROOF: The second term of equation (8), $b_h q_h^2$, represents the present value of price impact costs in dollars. Dividing it by q_h and substituting q_h by q_h^* from equation (13) gives $b_h q_h^* = a_h/2$. □

Equation (18) shows that, holding q_h constant, the price impact costs ($PI_h = b_h q_h$) are higher for a fund investing in short-term than long-term opportunity owing to Corollary 1 ($b_S > b_L$).

Proposition 2 also implies that, in equilibrium, the magnitude of price impact costs depends only on the fund's alpha opportunity under the quadratic cost function. This is because the optimal amount of capital invested q_h^* is determined by the fund's horizon-specific skill (value added), which takes fund turnover and price impact costs b_h into account. The fund would trade and pay price impact costs only if there is an alpha opportunity ($a_h > 0$) to profit from.

PROPOSITION 3: *If $\hat{J}_S^* > \hat{J}_L^*$, then $a_S > a_L$. If $\hat{J}_L^* > \hat{J}_S^*$, this does not necessarily imply that $a_L > a_S$.*

PROOF: If the fund chooses short-term opportunities ($\hat{J}_S^* > \hat{J}_L^*$), then equation (17) should be true. This implies

$$a_S > a_L \sqrt{\frac{b_S}{b_L}} > a_L, \tag{19}$$

where the second inequality is due to Corollary 1. If the fund chooses long-term opportunities, we have

$$a_L > a_S \sqrt{\frac{b_L}{b_S}}, \tag{20}$$

which gives the desired result. □

This proposition shows that the fund invests in short-term opportunities because of its higher short-term alpha. However, the fund may invest in long-term opportunities because of either its higher long-term alpha before price impact costs or its cost advantage in the case of investing over a longer term.

We now summarize the main predictions relevant to our empirical analyses.[17]

PREDICTION 1: Fund turnover correlates positively with short-term value added and negatively with long-term value added.

PREDICTION 2: Fund turnover correlates positively with price impact costs controlling for fund size.

PREDICTION 3: Fund turnover correlates positively with the abnormal returns of the fund's short-term holdings before price impact costs.

II. Decomposition Method

We decompose funds' daily value added into the value added from holdings shorter than a year (net purchases in the past 1 to 240 days) and the value added from holdings longer than a year.[18]

A fund's value added on day t can be expressed as the sum of the value added from its holdings at the beginning of day t and the value added from its trades on day t after price impact costs,

$$VA_t = \sum_i H_{i,t-1} R_{i,t} + \sum_i V_{i,t} R^e_{i,t}, \tag{21}$$

where $H_{i,t-1}$ is the fund's holding of stock i at the end of day $t-1$ in dollars. For $R_{i,t}$, we use abnormal returns based on the CAPM in the benchmark analysis, and we use the FF3 and FF4 in robustness analyses.[19] The variable $V_{i,t}$ is the fund's trading amount of stock i on day t, which is positive for purchases and negative for sales, and $R^e_{i,t}$ is defined as

$$R^e_{i,t} = (P^c_{i,t} - P^e_{i,t})/P^e_{i,t}, \tag{22}$$

where $P^e_{i,t}$ is the execution price and $P^c_{i,t}$ is the closing price for stock i on day t. As for $R_{i,t}$, we adjust $R^e_{i,t}$ based on the CAPM (as well as the FF3 and FFC4). Since the exact time of trade execution within a day is not reported in the Ancerno data set, we assume that on average trades occur at midday when adjusting $R^e_{i,t}$. Given that the daily risk premia are negligible, this does not materially affect our results. For example, the contribution of trades to fund value

[17] Since the parameter for price impact cost λ is a constant in our one-fund model, empirical predictions on price impact costs and abnormal returns are made under the assumption that λ is properly controlled for in the cross-sectional analysis of funds. The prediction on value added does not rely on this assumption considering that the value-added measure has already accounted for λ.

[18] We choose one year as the maximum time horizon because, on average, funds stay in the Ancerno database for about three years.

[19] The alphas of stocks are calculated using one-year rolling regressions at a daily frequency. One reason to use the CAPM as the benchmark model is that fund investors care about CAPM alphas, not multifactor alphas, as documented by Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016).

added through market exposure within the same day is approximately USD 9,000 per year, which is only 0.1 basis points (bps) of the average funds' total net assets (TNAs) and 2 bps of average value added of funds in our sample.

In summary, the first term on the right-hand side of equation (21) is the contribution of the holdings at the end of day $t-1$ to fund value added on day t, and the second term is the contribution of the trades on day t to the same-day fund value added.

We denote the change in holdings caused by trades within the past n days (10 to 240 days) by $H^{s(n)}_{i,t-1}$, and we further denote net purchases over the past n days by

$$B^{s(n)}_{i,t-1} = \begin{cases} 0, & \text{if } H^{s(n)}_{i,t-1} \leq 0, \\ H^{s(n)}_{i,t-1}, & \text{if } H^{s(n)}_{i,t-1} > 0. \end{cases} \tag{23}$$

Similarly, we denote the net purchase of stock i on day t by

$$B_{i,t} = \begin{cases} 0, & \text{if } V_{i,t} \leq 0, \\ V_{i,t}, & \text{if } V_{i,t} > 0. \end{cases} \tag{24}$$

We denote net sales over the past n days by $S^{s(n)}_{i,t-1}$ and net sales on day t by $S_{i,t}$. We therefore have

$$H^{s(n)}_{i,t-1} = B^{s(n)}_{i,t-1} + S^{s(n)}_{i,t-1}, \tag{25}$$

and

$$V_{i,t} = B_{i,t} + S_{i,t}. \tag{26}$$

A fund's holdings at the end of day $t-1$, $H_{i,t-1}$, can then be decomposed into holdings shorter than n days (the net purchase over the past n days), $B^{s(n)}_{i,t-1}$, and holdings that have been in the portfolio longer than n days, $H^{l(n)}_{i,t-1}$:[20], [21]

$$H_{i,t-1} = B^{s(n)}_{i,t-1} + H^{l(n)}_{i,t-1}. \tag{27}$$

Substituting equations (26) and (27) into equation (21) gives

$$VA_t = \left(\sum_i B_{i,t}R^e_{i,t} + \sum_i B^{s(n)}_{i,t-1}R_{i,t}\right) + \sum_i H^{l(n)}_{i,t-1}R_{i,t} + \sum_i S_{i,t}R^e_{i,t}, \tag{28}$$

where the fund's value added on day t is decomposed into value added from holdings shorter than n days (the first two terms in parentheses) and value

[20] Please refer to Table A1 for the fraction of holdings by past length of holding periods and by fund categories.

[21] For the sake of accuracy, $H^{l(n)}_{i,t-1}$ is the holding that was already in the fund's portfolio n days ago and is still in the fund's portfolio at the end of day $t-1$. This measure of holding longer than n days takes the shares sold and bought back shortly thereafter into account. Our result is almost the same if we instead measure it using shares that were always in the portfolio over the past n days.

added from holdings longer than n days (the third term).[22] The last term adjusts for stocks sold on day t. The effect of sales on the daily value added of a fund is, on average, USD 0.22 million per year based on the CAPM, which is only 2.1 bps of the average fund TNAs,[23] therefore including or eliminating it does not affect our results. Since for each day t, holdings shorter than n days are still in the fund's portfolio and will only be sold at a later date, adding the costs (or profits) of all sales (including the sales of holdings longer than n days) to the value added of holdings shorter than n days would overestimate the importance of such sales to the short-term value-added measurement. If instead one assumed that all of these holdings are sold on day t anyway, one can add this term for the calculation of value added from holdings shorter than n days. This does not have a significant effect on our findings.

Here, we use a numerical example to illustrate our method of decomposing value added by investment horizon as described in equation (28). Imagine we have a fund. On September 30, 2002, the fund has 100 shares of IBM in its portfolio purchased 40 days ago (with a holding period of 40 days) and 200 shares of MSFT in its portfolio purchased 300 days ago (with a holding period of 300 days). On that day, the fund newly purchased 20 shares of GM (with a holding period of 0). On September 30, 2002, IBM's CAPM-adjusted return is 1%, and MFST's CAPM-adjusted return is 2%. GM's CAPM-adjusted return from the execution of the trade to the end of the day is 3%. The price of IBM is 58 dollars per share at the end of September 29, 2002, and the price of MSFT is 43 dollars per share. The execution price of the purchases of GM on September 30, 2002 is 38 dollars per share. The information above is summarized in the table below.

Ticker	$P^e_{i,t}$	$P_{i,t-1}$	Num. of Shares	Holding Period	$R_{i,t}$	$R^e_{i,t}$
IBM		58	100	40	1%	
MSFT		43	200	300	2%	
GM	38		20	0		3%

Now we decompose the fund's value added on September 30, 2002 into value added from holdings shorter than 10 days, which includes new purchases on

[22] One may argue that if funds hold onto winning positions and sell losing positions, the winning positions will have long investment horizons and create large value added automatically. In this case, the investment horizon and the value added of a position are endogenously related. Although this argument is true for the total value added of a position over its entire investment horizon, this argument is not true for its value added per day used in this study (equations (21) and (28)). Under the null that the fund has no skill, there is no reason the value added of a holding on a specific day would be related to the past length of that fund's holding.

[23] A positive effect of sales on the daily value added of a fund means that intraday profits of sales more than cover their price impact costs.

the same day, and value added from holdings longer than 10 days,

$$VA^{s(10)} = 20 \times 38 \times 3\% = 22.8,$$

$$VA^{l(10)} = (100 \times 58 \times 1\% + 200 \times 43 \times 2\%) = 230.$$

The same calculation applies to value added from holdings shorter/longer than 20 and 30 days in this example. In addition, we can decompose the fund's value added on September 30, 2002 into value added from holdings shorter than 240 days and value added from holdings longer than 240 days,

$$VA^{s(240)} = (20 \times 38 \times 3\% + 100 \times 58 \times 1\%) = 80.8,$$

$$VA^{l(240)} = 200 \times 43 \times 2\% = 172.$$

The same calculation method applies if the 200 shares purchased 300 days ago are IBM instead of MSFT.

III. Mutual Fund Data and Measures of Trading Costs

A. *Mutual Funds Sample*

To construct the daily holdings data of mutual funds, we merge three databases: transaction data provided by Abel Noser Solutions (also known as Ancerno data), quarterly holdings data in the Thomson Reuters database, and fund characteristics from the CRSP mutual fund database.

Abel Noser Solutions is a consulting firm that works with institutional investors to analyze their trading costs. Their clients include hedge funds, pension funds, and mutual funds. The data set that we obtained contains detailed information regarding trading amounts, trading times, and trading costs. One drawback is that the data set does not disclose the actual identities of the funds.[24] We identify the mutual funds in this data set by matching the changes in the stock holdings indicated by the transaction data in Ancerno with the changes in the holdings reported in Thomson Reuters following the method developed by Busse et al. (2021). We further match these Thomson Reuters funds to the CRSP mutual fund data and keep active equity funds for our analysis. We manually verify the identified matches one by one using fund names from Thomson Reuters and the CRSP mutual fund database, and a list of client manager names disclosed by Ancerno in 2011.

We end up with 331 active equity funds that are properly matched for our analysis (please refer to the Internet Appendix for details on the matching procedures and quality).[25] These 331 funds belong to 48 fund-managing firms with 6.9 funds in each managing firm on average.

[24] However, a unique identifier is assigned to each institutional investor between 1999 and 2010.

[25] The Internet Appendix may be found in the online version of this article. The percentage of Thomson Reuters quarterly holdings matched with Ancerno transaction data for our sample of mutual funds is higher than that reported in the appendix of Puckett and Yan (2011) for 68 institutions for which they obtained a complete name list from Ancerno.

We construct the daily holdings of the 331 mutual funds by merging the transaction data in Ancerno with the quarterly holdings data in Thomson Reuters. If the stock's prior-quarter holding exists, we generate the daily holding on the basis of the holding at the end of the prior quarter and combine it with transactions in the current quarter. If the prior-quarter holding does not exist, we use the holding at the end of the current quarter and combine it with the transactions in the current quarter to generate the daily holding.[26]

To confirm that our finding can be generalized to a larger sample of mutual funds, we hand collect the monthly holdings data of U.S. equity mutual funds from Morningstar Direct and merge them with the CRSP mutual fund database.[27] We end up with 2,492 U.S. equity mutual funds from 1993 to 2020 for this analysis. We exclude fund-years with only quarterly or semiannual holdings from our analysis.

Panel A of Table I reports summary statistics for the 331 mutual funds with daily holdings data and summary statistics for 2,492 mutual funds with monthly holdings data from Morningstar. The characteristics of the 331 funds are similar to the characteristics of 2,492 mutual funds with monthly holdings data.[28] The average fund turnover and expense ratio of these 331 funds are slightly higher than those of 2,492 funds mainly because the mutual fund industry becomes more passive and charges lower fees after 2010 in aggregate. In addition, the average value-weighted fund net return of these 331 is 5.15% per year, close to the 4.94% per year for all equity mutual funds in the CRSP mutual fund database in the same period. The main difference is that these 331 funds are, on average, larger than the 2,492 mutual funds with monthly holdings data in 2001 and 2005. Ancerno's clients are more likely to be large funds than small funds. This difference is also documented by other studies using Ancerno data, such as Puckett and Yan (2011), who also provide evidence that institutions are not submitting their trades to Ancerno selectively.[29]

B. Measures of Price Impact Costs and Other Trading Costs

We measure the contributions of both explicit and implicit trading costs to fund value added. Explicit trading costs include commissions, taxes, and fees. Implicit trading costs include the intraday implicit costs related to the price impact of trades.

Trades' commissions, taxes, and fees are reported directly in Ancerno in dollars. We calculate their (negative) contribution to daily fund value added as the average dollar amount of those costs per day. We measure the intraday price

[26] Please refer to the Internet Appendix for more details on the construction of daily holdings.

[27] We hand collect the data because Morningstar Direct has a daily limitation on the number of observations that can be downloaded. Monthly holdings data become available starting in 1993. The detailed procedure for merging the Morningstar database and the CRSP mutual fund database is available in the Internet Appendix of Berk and van Binsbergen (2015).

[28] The characteristics of all U.S. equity mutual funds in the CRSP mutual fund database are similar to those of the 2,492 mutual funds with monthly holdings data.

[29] See the appendix of Puckett and Yan (2011).

Table I
Summary Statistics

Panel A reports summary statistics for 331 funds with daily holdings data from 1999 to 2010 (Panel A1) and 2,492 funds with monthly holdings data in Morningstar from 1993 to 2020 (Panel A2). *Year* is the year of the record. *Num. of Funds* is the number of funds in the sample. *Fund TNAs* ($mn) is the average fund TNAs in million dollars aggregated across different share classes (*crsp_fundno*). Other variables are averaged across share classes. *Stock Holding* (*Cash Holding*) is equity (cash) holdings as a percentage of fund TNAs as reported in CRSP, which are mostly missing before 2002. *Turnover* (%) is annual turnover reported in CRSP, which is the minimum of aggregate purchases and aggregate sales during the calendar year divided by the average TNAs of the fund. *Expense Ratio* (%) is the annual expense ratio and *Management Fee* (%) is the management fee. *Fund Age* is the average fund age. Panel B reports summary statistics for variables used in regression analysis at the fund level (*wficn*). *VA n* is the annualized daily value added of holdings shorter than n (1 to 20) days in million dollars, and *VA 240+* is value added from holdings longer than 240 days. *ES all/buy/sell* is the execution shortfall of all trades/purchases/sales in bps. *Alpha n* is the daily alpha of holdings shorter than n (1 to 20) days before price impact costs in bps. Control variables at the fund-quarter level include expense ratio *Exp ratio(%)*, fund age *Age*, quarterly fund flow *Flow* as a fraction of fund TNAs, and past-year fund return *Ret pastly*.

Panel A: Summary Statistics for Funds								
Year	Num. of Funds	*Fund TNAs* ($mn)	*Stock Holding* (%)	*Cash Holding* (%)	*Turnover* (%)	*Expense Ratio* (%)	*Management Fee* (%)	*Fund Age*
A1: 331 funds with daily holdings data								
1999–2010	331	1,733	92.4	3.6	98.0	1.50	0.70	8.0
2001	94	1,570	–	–	127.3	1.62	0.71	6.1
2005	208	2,108	93.4	4.1	96.6	1.52	0.70	7.5
2010	79	611	89.7	3.2	80.4	1.41	0.73	8.4
A2: 2,492 Funds with Monthly Holdings Data in Morningstar								
1993–2020	2,492	1,578	94.2	2.9	78.8	1.38	0.72	10.25
2001	1,855	1,040	–	–	105.9	1.57	0.75	6.2
2005	2,033	1,193	96.0	3.1	83.7	1.52	0.74	7.4
2010	1,661	1,256	93.8	2.7	76.5	1.39	0.72	10.1

(*Continued*)

Table I—*Continued*

Panel B: Summary Statistics for Regression Variables

Variable	# Obs.	Mean	Std.Dev.	p5	p25	p50	p75	p95
B1: Value Added, Execution Shortfall, and Alpha (Daily)								
VA 1	210,924	1.1	55.2	−13.0	−0.1	0.0	0.4	17.4
VA 2	210,747	1.1	73.8	−21.0	−0.4	0.0	0.8	26.0
VA 5	209,589	1.6	114.7	−41.2	−1.6	0.0	2.4	48.6
VA 10	207,664	2.0	178.1	−71.4	−3.9	0.0	4.8	78.7
VA 20	203,839	2.5	276.8	−115.0	−7.5	0.0	8.8	126.7
VA 240+	128,167	27.5	3,270.9	−1,485.1	−97.3	0.5	104.1	1,548.6
ES all	130,656	6.7	124.8	−180.9	−35.2	5.9	48.4	192.9
ES buys	106,642	4.5	138.7	−211.5	−44.9	4.8	55.5	216.8
ES sells	103,726	10.5	142.0	−199.6	−38.3	5.8	55.4	233.0
Alpha 1	129,376	16.2	181.1	−228.9	−56.2	9.5	82.8	281.1
Alpha 2	142,936	12.6	170.8	−216.6	−54.6	6.9	75.4	257.0
Alpha 5	164,943	8.6	148.3	−191.4	−50.3	4.4	63.6	220.4
Alpha 10	180,441	5.5	131.7	−171.1	−46.9	2.8	55.0	191.6
Alpha 20	189,367	3.6	113.2	−150.8	−42.3	1.8	47.8	164.3
B2: Other Fund Characteristics (Quarterly)								
Exp ratio (%)	2,485	1.27	0.46	0.47	0.99	1.25	1.55	2.10
Age	2,624	11.8	11.4	2.2	5.2	8.7	14.2	33.6
Flow	2,750	0.012	0.123	−0.113	−0.043	−0.011	0.029	0.218
Ret pastly	2,717	0.058	0.223	−0.343	−0.049	0.076	0.176	0.418

impact costs using the execution shortfalls of trades. The execution shortfall is the difference between the actual execution price of a stock and the price at the time of order placement (measured by the last executed price of the same stock) as a percentage of the price at the time of order placement.[30] The expression is

$$ES_{i,t} = D_{i,t}\frac{P^e_{i,t} - P^0_{i,t}}{P^0_{i,t}}, \tag{29}$$

where $D_{i,t}$ is 1 for buys and -1 for sells, $P^0_{i,t}$ is the stock price at order placement, and $P^e_{i,t}$ is the order's actual execution price. If you buy (sell) at a price $P^e_{i,t}$ higher (lower) than $P^0_{i,t}$, the price impact cost of this trade as measured by $ES_{i,t}$ is positive. The execution shortfall can be positive or negative depending on market conditions, and the extent to which an order demands or supplies liquidity. Following Anand et al. (2012), we drop from our analysis execution shortfalls with an absolute value larger than 10%. The intraday price impact costs measured by the execution shortfalls are paid during trade executions. The total contribution of intraday price impact costs to a fund's daily value added for all trades on day t is

$$ES_t = \sum_{i=1}^{I}(D_{i,t}V_{i,t}ES_{i,t}), \tag{30}$$

with the intraday price impact costs of each trade in dollars calculated as the product of the absolute trading amount, $D_{i,t}V_{i,t}$, and the execution shortfall, $ES_{i,t}$.

IV. Decomposing Value Added by Investment Horizon

In this section, we analyze the average value added of holdings by investment horizon and its variation in the cross section of funds by fund turnover, as well as fund size, to test our model predictions. We investigate their actual holdings (i.e., net purchases) based on the past length of their holding periods. We show that, consistent with our model predictions, funds possess skills at different investment horizons, and they choose the type of opportunities to invest in based on their horizon-specific skills (value added), which takes heterogeneous price impact costs of investing at different investment horizons into account.

A. Value Added of Low-Turnover versus High-Turnover Funds

We first investigate whether there are funds that add value through their short-term investment skills (with $\hat{J}^*_S > 0$ in equation (15)), and funds that

[30] Although the exact execution time of a trade is not available in Ancerno, the execution price and the price at the time of order placement are available for each trade.

profit from their long-term investment skills (with $\hat{J}_L^* > 0$). Our model suggests that high-turnover funds that optimally choose to invest in short-term investment opportunities S (since $\hat{J}_S^* > \hat{J}_L^*$ according to Proposition 1) are more likely to have short-term skills ($\hat{J}_S^* > 0$), and low-turnover funds that optimally choose to invest in long-term investment opportunities L are more likely to have long-term skills ($\hat{J}_L^* > 0$). Therefore, we study the value added of high- and low-turnover funds separately. For each of these two categories, we then study separately their short-term and long-term holdings. In particular, we focus on the following questions. First, we address whether the short-term (long-term) holdings of high-turnover (low-turnover) funds add value after price impact costs. Second, we study whether the short-term holdings of high-turnover funds add more value than the short-term holdings of low-turnover funds, and vice versa (Prediction 1). Third, we study the sources of their profits at different investment horizons.

A.1. Fund Turnover Dispersion and Persistence

We sort funds into quintiles based on their average turnover every quarter. Table II reports the average value added of funds, fund characteristics, trading costs, and stock characteristics (average within the turnover quintile) for each turnover quintile. The dispersion in fund turnover is large across turnover quintiles. As reported in Panel B, the total turnover for both purchases and sales varies from 29% of fund TNAs per year (for quintile 1) to 807% (for quintile 5), that is, funds in the low-turnover quintile change their portfolio once every six to seven (= 1/(29%/2)) years on average, whereas funds in the high-turnover quintile change their portfolio about four (= 807%/2) times per year. This result indicates that low-turnover funds and high-turnover funds target profits at very different investment horizons. Figure 1 plots the average turnover of funds for each turnover quintile in the current quarter (Q+0) and in the following three years (Q+1 to Q+12).[31] As Figure 1 shows, funds' turnover is highly persistent over time, especially for high-turnover funds in quintile 5. While the average turnover for quintiles 1, 2, 3, and 4 converge slowly toward each other in the following three years, the average turnover of funds in quintile 5 stays above five times the fund TNAs per year.

A.2. Value Added of Holdings by Investment Horizon

Next, we test whether the value added of high-turnover funds' short-term holdings are significantly positive after price impact costs (with $\hat{J}_S^* > 0$ in equation (15)) and whether the value added of low-turnover funds' long-term holdings are significantly positive ($\hat{J}_L^* > 0$).

Table III reports the value added of holdings shorter than 240 days (net purchases within 240 days) calculated using equation (28) and their significance levels. As shown in columns (5) to (8) of Table III for high-turnover

[31] The turnover quintiles are constructed at Q + 0, and their average turnover is tracked over the following three years from Q + 1 to Q + 12.

Table II

Value Added, Fund Characteristics, and Trading Costs by Fund Turnover Quintile

This table reports the fund value added, fund characteristics, trading costs, and characteristics of holdings for all funds and by funds' turnover quintile. We sort funds every quarter into quintiles based on the turnover of funds including both purchases and sales. Panel A reports the total value added based on the CAPM and value added from holdings shorter than 240 days (net purchases in the past 240 days) and beyond 240 days using equation (28). The fraction of value added from holdings beyond 240 days, row Fraction, and the total value added based on the Fama-French three-factor model (FF3) and the Fama-French-Carhart four-factor model (FFC4) are also reported. Panel B reports fund characteristics. *Expenses* are the product of the expense ratio and fund TNAs in million dollars. Panel C separately reports the trading costs for commissions, taxes and fees, and execution shortfalls. Panel D reports the average stock characteristic quintile of funds' holdings. All numbers in this table are annualized and equally weighted across all fund-day observations, and all value added as well as trading costs are reported in million dollars. Robust standard errors are clustered at the day level. Significance level: ***0.01, **0.05, and *0.1.

		Turnover Quintile				
	All Funds	1 Low	2	3	4	5 High
Panel A: Value Added of Funds						
Value added (CAPM)	35.9***	67.5*	64.2***	25.6*	2.6	6.3
From holdings <240 days	4.9**	4.4	2.6	7.4*	0.5	10.7
From holdings >240 days	31.0***	62.9*	61.5***	18.0	1.8	−3.1
Fraction	*0.86*	*0.93*	*0.96*	*0.70*	*0.69*	*−0.65*
Value added (FF3)	12.0	5.7	32.0*	18.6*	0.3	1.1
Value added (FFC4)	17.1*	24.1	39.4**	19.6*	−2.6	−1.0
Panel B: Fund Characteristics						
Expense ratio (in %)	1.37	1.16	1.42	1.39	1.42	1.45
Expenses (in million dollars)	8.8	13.5	8.5	10.2	6.7	5.1
Turnover (buy + sell, in %)	247	29	78	136	238	807
TNAs (in million dollars)	1,076	2,306	1,014	970	588	412
Panel C: Trading Costs						
Explicit costs						
- Commissions	1.9***	0.8***	1.2***	1.9***	1.7***	4.2***
- Taxes and fees	0.2***	0.0***	0.1***	0.2***	0.3***	0.2***
Implicit costs (deducted)						
- Execution shortfall	3.0***	−0.5***	0.2	1.1***	2.1***	13.0***
Total	5.1***	0.3**	1.5***	3.2***	4.1***	17.4***
Panel D: Average Stock Characteristic Quintile of Holdings						
BM ratio quintiles	3.0	3.3	3.1	3.0	2.8	2.6
Stock-cap quintiles	3.0	3.1	3.1	3.0	3.0	2.7
Momentum quintiles	2.9	2.6	2.6	2.8	3.2	3.6

funds in quintile 5, their holdings shorter than 1/2/5 days add USD 2.6/2.3/2.9 million of value per year (0.64%/0.55%/0.71% in terms of annual gross alpha) under the CAPM, which is statistically significant at the 1% significance level. These numbers are only slightly smaller under the FF3, the FFC4, and the

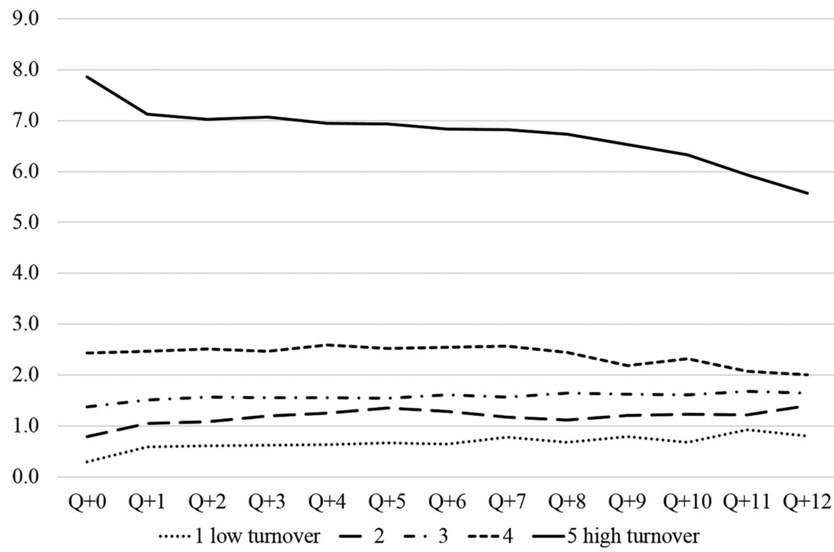

Figure 1. Persistence of fund turnover. This figure plots the average turnover of funds for each turnover quintile in the following three years. The turnover plotted here is annualized quarterly turnover including both purchases and sales, calculated as the total trading volumes of purchases and sales divided by fund TNAs. The solid line at the top corresponds to funds with the highest turnover (quintile 5) and the dotted line at the bottom to funds with the lowest turnover (quintile 1). Fund turnover is winsorized at 1% level.

Fama-French-Carhart four-factor + Pastor-Stambaugh liquidity factor model (FFC+Liq), and they stay significantly positive at the 5% significance level. In addition, high-turnover funds' holdings shorter than 10/20/40 days add USD 3.3/4.2/6.6 million of value per year (0.81%/1.02%/1.61% in terms of annual gross alpha) under the CAPM, which is statistically significant at the 10% significance level, and their holdings shorter than 240 days add as much as USD 10.7 million of value per year (2.59% in terms of annual gross alpha). In contrast, columns (1) to (4) of Table III report that low-turnover funds' holdings shorter than 1 to 40 days do not add value, and their holdings shorter than 240 days only add a statistically insignificant USD 4.4 million of value per year (0.19% in terms of annual gross alpha).[32]

The last two rows of Table III report the value added from holdings longer than 240 days and the total value added from all holdings. As reported in the

[32] As we discuss in Section II, if one were to assume that all holdings shorter than n days are sold on day t, one can include the last term of equation (28) in the calculation of value added from holdings shorter than n days. The effect of sales on daily value added is relatively small, at about USD 0.16 million per year (0.7 bps in terms of annual gross alpha) for low-turnover funds and USD -0.23 million per year (5.6 bps in terms of annual gross alpha) for high-turnover funds under the CAPM. Including it does significantly affect our results. Moreover, if the sales of high-turnover funds predict negative abnormal returns beyond a day, these sales add value by avoiding losses from holding stocks for a longer periods.

Table III

Value Added of Holdings: Low-Turnover Funds versus High-Turnover Funds

This table reports the value added from holdings shorter than (net purchases in the past) 240 days and the corresponding contribution to the fund's annual gross alpha for low-turnover funds and high-turnover funds separately. Funds are sorted into turnover quintiles according to their total turnover including both purchases and sales every quarter. Quintile 1 corresponds to low-turnover funds and quintile 5 to high-turnover funds. Panel A reports the value added from net purchases in the past n (1 to 240) days, which is calculated using equation (28). We separately use CAPM (CAPM), Fama-French three-factor (FF3), Fama-French-Carhart four-factor (FFC4), Fama-French-Carhart four-factor + Pastor-Stambaugh liquidity factor (FFC+Liq) abnormal returns of each stock for this calculation. Day 0 is for value added of purchases on the same day. Value added of all holdings (i.e., value added of a fund) is also reported in the All holdings row, and value added from holdings that have been in the portfolio longer than 240 days is the difference between value added of all holdings and value added of net purchases within 240 days. Panel B reports the corresponding contribution to the fund's annual gross alpha, which is the value added divided by the fund TNAs. Value added is equally weighted across fund-day observations and the corresponding contribution to fund return is value weighted by fund TNAs. Both value added and gross alpha are annualized. Robust standard errors are clustered at the day level. Significance level: ***0.01, **0.05, and *0.1.

	Low-Turnover Funds (Q1)				High-Turnover Funds (Q5)			
	CAPM	FF3	FFC4	FFC+Liq	CAPM	FF3	FFC4	FFC+Liq
Day	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Value Added of Purchases (in million dollars)								
0	0.3***	0.2***	0.3***	0.3***	1.4***	1.3***	1.3***	1.2***
1	0.0	0.0	0.0	0.0	2.6***	2.4***	2.1***	2.3***
2	0.1	0.0	0.0	0.0	2.3***	1.9***	1.6**	2.1***
5	0.3	0.2	0.2	0.2	2.9***	2.4**	2.0**	2.5***
10	0.4	0.2	0.3	0.2	3.3**	2.6*	1.7	2.2*
20	0.3	0.3	0.2	0.2	4.2*	2.8	1.4	2.3
40	0.1	−0.2	0.1	0.2	6.6*	4.3	2.5	3.7
60	3.6	2.6	2.5	2.5	5.7	5.2	2.6	3.1
120	6.6*	5.4	4.7	4.9	5.6	5.9	0.5	1.5
240	4.4	2.1	4.5	4.3	10.7	9.3	4.4	3.5
>240	62.9*	3.4	19.4	24.2	−3.1	−7.0	−4.3	−2.7
All holdings	67.5*	5.7	24.1	28.4	6.3	1.1	−1.0	0.8
Panel B: Contribution to Fund's Annual Gross Alpha (in %)								
0	0.01***	0.01***	0.01***	0.01***	0.35***	0.32***	0.31***	0.29***
1	0.00	0.00	0.00	0.00	0.64***	0.58***	0.52***	0.56***
2	0.00	0.00	0.00	0.00	0.55***	0.47***	0.40**	0.51***
5	0.02	0.01	0.01	0.01	0.71***	0.57**	0.48**	0.60***
10	0.02	0.01	0.01	0.01	0.81**	0.62*	0.40	0.54*
20	0.01	0.01	0.01	0.01	1.02*	0.67	0.33	0.55
40	0.01	−0.01	0.00	0.01	1.61*	1.03	0.62	0.89
60	0.16	0.11	0.11	0.11	1.37	1.26	0.64	0.76
120	0.28*	0.23	0.21	0.21	1.37	1.42	0.13	0.37
240	0.19	0.09	0.20	0.18	2.59	2.26	1.06	0.86
>240	2.73*	0.15	0.84	1.05	−0.75	−1.70	−1.04	−0.65
All holdings	2.93*	0.25	1.05	1.23	1.54	0.26	−0.24	0.20

second to last row of column (1) in Table III, Panel A, low-turnover funds' holdings longer than 240 days add a significant USD 62.9 million of value per year (2.73% in terms of annual gross alpha) using the CAPM as the benchmark, which accounts for 93% (= 62.9/67.5) of their total value added. In contrast, high-turnover funds' holdings longer than 240 days destroy USD 3.1 million of value (−0.75% in terms of annual gross alpha), which is not statistically different from zero.

The fact that short-term holdings of high-turnover funds add a significant amount of value, whereas short-term holdings of low-turnover funds add no value supports the first part of Prediction 1, which states that there is a positive correlation between fund turnover and short-term value added. Our finding that long-term holdings of low-turnover funds add substantial value whereas long-term holdings of high-turnover funds add no value confirms the second part of Prediction 1, which states that there is a negative correlation between fund turnover and long-term value added. These results suggest that a fund's horizon-specific skill is an important determinant of its choice of investment opportunities. Moreover, we show that the total value added of high-turnover funds is not statistically different from zero because of the relatively low (or volatile) value added of their holdings at longer horizons.[33]

To understand the sources of funds' value added at different investment horizons, in Table III, we compare the results under the CAPM with those under FF3, FFC4, and FFC+Liq. By comparing low-turnover funds' value added based on CAPM, in column (1), to that based on FF3, in column (2), we find that low-turnover funds' value added from holdings longer than 240 days essentially disappear after controlling for the size and value factors (decreasing from a significant USD 62.9 million per year to an insignificant USD 3.4 million per year). That is, the majority of low-turnover funds' value added from holdings longer than 240 days are explained by their exposure to the size factor or the value factor. Since the average holdings of low-turnover funds tilt toward value stocks and large-cap stocks (as reported in Table II, Panel D), their value added from long-term holdings comes mainly from exposure to the value factor, not the size factor. Considering that the value strategy is a long-term strategy with a low turnover rate, this result indicates that low-turnover funds mainly use a value strategy (or strategies highly correlated with the value factor) to harvest long-term alphas. In addition, columns (5) to (7) of Table III show that high-turnover funds' value added from net purchases within 240 days do not change much after controlling for the size and value factors (under FF3), but reduce substantially after controlling for the momentum factor (under FFC4), except for the USD 1.3 million of value added on the trading day (day 0). Since the momentum strategy is a short-term strategy with a high turnover rate, this result indicates that high-turnover funds partially use momentum (or strategies highly correlated with momentum)

[33] This result reconciles our finding and the findings in Cremers and Pareek (2016) and Lan, Moneta, and Wermers (2023) that high-turnover (short-duration/horizon) funds do not outperform their benchmarks before expenses.

to harvest short-term alphas.[34] It is worth noting that the value added from high-turnover funds' holdings shorter than five days is not well explained by the momentum factor (as reported in Table III), indicating that high-turnover funds add value using strategies at a higher frequency than momentum. Furthermore, after including the Pastor-Stambaugh liquidity factor in the model (comparing columns (7) and (8)), we find that high-turnover funds' value added from holdings shorter than 1 to 60 days increases rather than decreases. This result indicates that high-turnover funds, on average, have negative exposure to the Pastor-Stambaugh liquidity factor. Thus, high-turnover funds lose value from consuming liquidity, rather than add value from providing liquidity.[35]

Table IV, Panel A further reports the value added using the CAPM as the benchmark for all five turnover quintiles. The results consistently show that the short-term value added within two weeks largely increases with turnover quintiles, whereas the long-term value added beyond a year decreases with turnover quintiles. We compare the value added of high-turnover (Q5) funds and low-turnover (Q1) funds at each investment horizon and report the results in Panel B of Table IV. Columns (2) and (3) show that high-turnover funds have significantly higher value added than low-turnover funds for holdings shorter than 40 days, and low-turnover funds have significantly higher value added than high-turnover funds for holdings longer than 240 days. The differences in their value added are small and insignificant for medium holding periods (60, 120, and 240 days).

However, the distribution of value added features excess kurtosis as mentioned in Berk and van Binsbergen (2015)—although our sample has more than 2,000 days in 10 years, it might not be large enough to ensure that the t-statistics are t-distributed. Therefore, we also use an alternative measure of statistical significance based on the order statistics developed in Berk and van Binsbergen (2015). This measure is more powerful, since it does not rely on any large sample or asymptotic properties of the distribution. Specifically, we count the fraction of times (days) that the average value added of high-turnover funds is larger than that of low-turnover funds for each holding period, and test it against the null hypothesis that this fraction is 50% or lower (higher) for the first (second) part of Prediction 1. Under this measure (as reported in columns (4) and (5) of Table IV, Panel B), the null hypothesis of the first part of Prediction 1 is rejected at the 95% confidence level for holdings shorter than 60 days, and the null of the second part is rejected at the 95% confidence level for holdings longer than 240 days.

[34] Since the value and momentum factors do not take into account the price impact costs of trades (as shown in Patton and Weller (2020)), whereas our value-added measure does, the value added attributable to the value and momentum strategies may be smaller.

[35] In the Internet Appendix, we document funds' value added from factor premia (i.e., from exposures to momentum, value, and liquidity factors) by turnover quintiles and their significance. Furthermore, we sort funds by their exposures to value and momentum factors and document that funds with high exposure to the momentum factor earn most of the momentum premium within six months, and funds with high exposure to the value factor earn most of the value premium beyond a year. These results are consistent with the findings in Conrad and Kaul (1998).

Table IV

Value Added of Holdings by Turnover Quintile

This table reports the value added from holdings shorter than (net purchases in the past) 240 days and the corresponding contribution to the fund's annual gross alpha by turnover quintile. Funds are sorted into turnover quintiles according to their total turnover including both purchases and sales every quarter. Quintile 1 is for low-turnover funds and quintile 5 is for high-turnover funds. Panel A reports the value added from net purchases in the past n (1 to 240) days, which is calculated using equation (28) using CAPM abnormal returns (CAPM). Day 0 is for value added of purchases on the same day, and row ">240" is for value added from holdings that have been in the portfolio longer than 240 days. Panel B reports the average differences in value added between high-turnover funds (quintile 5) and low-turnover funds (quintile 1) by the past length of holding periods, and their associated p-values. The differences are averaged across days. We also report the fraction of days that high-turnover funds have a higher value added than low-turnover funds and their associated p-values. All p-values are one-tailed, that is, they represent the probability of the observed test statistic value greater (lesser) for holdings shorter (longer) than 240 days, under the null hypothesis that the value added of high-turnover funds is equal to or less (more) than that of low-turnover funds for holdings shorter (longer) than 240 days. Value added is equally weighted across fund-day observations and annualized. Robust standard errors are clustered at the day level. Significance level: ***0.01, **0.05, and *0.1.

Panel A: Value Added by Turnover Quintiles (in million dollars)

	Turnover Quintile				
Day	1 Low	2	3	4	5 High
0	0.3***	0.6***	0.9***	0.9***	1.4***
1	0.0	0.8***	1.1***	1.1***	2.6***
2	0.1	0.8***	1.3***	1.0***	2.3***
5	0.3	1.2***	1.9***	1.7***	2.9***
10	0.4	0.8	2.9***	2.4***	3.3**
20	0.3	0.6	4.3***	3.0**	4.2*
40	0.1	1.6	4.6**	3.0	6.6*
60	3.6	3.6*	6.1**	3.3	5.7
120	6.6*	4.7**	8.1**	2.3	5.6
240	4.4	2.6	7.4*	0.5	10.7
>240	62.9*	61.5***	18.0	1.8	−3.1

Panel B: Differences between Quintiles 5 and 1

	VA (5− 1)		Prob (5 > 1)	
Day	Mill Dollars	p-Value (%)	Freq. (%)	p-Value (%)
1	2.6***	0.00	52.09**	1.40
2	2.2***	0.10	51.57**	4.95
5	2.6***	0.80	51.89**	2.30
10	2.9**	4.15	52.21***	1.00
20	3.9*	7.35	52.86***	0.15
40	6.5*	6.90	52.07**	1.45
60	2.1	34.45	52.00**	1.75
120	−0.9	55.20	51.03	14.00
240	6.3	25.65	50.95	15.75
>240	−66.0**	4.10	48.43**	4.95

A.3. Double-Sorting by Fund Turnover and Fund Size Quintiles

Since fund skill (measured by total value added) and fund size are closely related in the cross section of funds (as predicted in equation (16)), we double-sort funds by fund size and turnover to control for the effect of skill level on value added at each investment horizon.[36] We sort funds into size quintiles based on their TNAs at the end of last quarter. We then construct 25 portfolios based on the intersections of these fund turnover and size quintiles. We report the value added from holdings shorter than 5, 10, and 20 days in Table V, Panels A, B, and C, respectively, and the value added from holdings longer than 240 days in Panel D.

As shown in Table V, the short-term value added (from holdings shorter than 5, 10, and 20 days in Panels A, B, and C) largely increases with turnover quintiles for all fund size quintiles. The differences between the short-term value added of high-turnover funds in Q5 and low-turnover funds in Q1 and Q2 are all positive, and 21 of 30 are statistically significant. These results confirm that our model prediction, that short-term holdings of high-turnover funds add more value than those of low-turnover funds, holds after controlling for fund size. We also find that long-term holdings of low-turnover funds in Q1 add more value than those of high-turnover funds in Q5 for four out of five fund size quintiles (as reported in Panel D). However, the difference is statistically significant only for large funds in Q5. Moreover, as predicted in equation (16), the short-term value added of high-turnover funds and the long-term value added of low-turnover funds increase almost monotonically with fund size.

A.4. Regression Analysis of Value Added on Fund Turnover

To confirm that our finding holds after controlling for different fund characteristics, we formally test our Prediction 1, which states that fund turnover correlates positively (negative) with short-(long-)term value added, using standard regression analyses. Specifically, we estimate

$$\begin{aligned} VA(n)_{j,t} = {} & \upsilon_t + b_1 * Turnover\,quintiles_{j,q-1} + b_2 * Fund\,size\,quintiles_{j,q-1} \\ & + b_3 * Stock\text{-}cap\,quintiles_{j,q-1} + b_4 * Exp\,ratio_{j,q-1} + b_5 * Age_{j,q-1} \\ & + b_6 * Flow_{j,q-1} + b_7 * Ret\,pastly_{j,y-1} + \varepsilon_{j,t}, \end{aligned} \tag{31}$$

where $VA(n)_{j,t}$ is the annualized value added of holdings shorter than n (1 to 20) days for each fund j on day t, and $VA\,(240+)_{j,t}$ is the value added of holdings longer than 240 days. We include one-quarter lagged turnover quintiles

[36] Equation (16) suggests that we should sort by the product of fund size and fees. Here, we follow the convention of the mutual fund literature and sort funds by fund size to make the results directly comparable with studies such as Busse et al. (2021). Since the variation in fees is substantially smaller than the variation in fund size in the cross section of funds, the result does not change much when we sort funds based on the product of fund size and fees. If we allow the fund to invest part of its capital in the passive benchmark as in Appendix Section B, we then have equation (B2) instead, but the same implication holds.

Table V

Value Added of Holdings Double-Sorted by Fund Size and Turnover Quintile

This table reports the value added from holdings shorter than (net purchases in the past) 5, 10, 20 days, and holdings longer than 240 days by fund size and turnover quintile. We sort funds into turnover quintiles according to their total turnover including both purchases and sales every quarter, and fund size quintiles based on their TNAs at the end of last quarter. The value added from holdings shorter than 5, 10, and 20 days is calculated using equation (28) and CAPM abnormal returns (CAPM). Panel A (B, C) reports the value added from holdings shorter than 5 (10, 20) days. Panel D reports the value added from holdings longer than 240 days. "(5−1)"("(5−2)") is the difference between turnover quintile 5 and 1(2) for each fund size quintile. Value added is equally weighted across fund-day observations and annualized. Robust standard errors are clustered at the day level. Significance level: ***0.01, **0.05, and *0.1.

(in million dollars)	Turnover Quintile						
Fund Size Quintile	1 Low	2	3	4	5 High	(5−1)	(5−2)
			Panel A: Value Added in 5 Days				
1 small	0.0*	0.0**	0.1	0.0	0.5**	0.5**	0.5**
2	0.0	0.1*	0.0	0.4***	0.7**	0.7**	0.6*
3	−0.3	−0.6*	0.5*	0.9**	1.5**	1.8***	2.2***
4	0.4**	0.9***	1.5*	2.8***	3.7**	3.3**	2.8*
5 large	0.9	4.7**	7.7***	5.4*	22.3*	21.4*	17.6
			Panel B: Value Added in 10 Days				
1 small	0.1	0.0	0.0	0.0	0.6*	0.5	0.5
2	0.0	0.2*	0.1	0.3*	1.4**	1.4**	1.3**
3	−0.9**	−1.1**	1.0***	1.1*	2.4***	3.2***	3.5***
4	0.5**	1.3**	2.4*	4.8***	3.4	2.9	2.1
5 large	1.4	3.0	11.1***	6.5	23.6	22.1	20.5
			Panel C: Value Added in 20 Days				
1 small	0.1	0.1	0.0	−0.2	1.3***	1.3***	1.3***
2	0.1	0.1	0.3*	0.6**	2.1**	2.0**	1.9**
3	−0.7	−0.3	1.6***	1.5	2.9**	3.6**	3.2**
4	0.2	2.3**	2.7	5.6**	9.2**	9.0**	6.8*
5 large	1.1	1.0	17.3***	8.8	17.1	15.9	16.1
			Panel D: Value Added from Holdings Longer than 240 Days				
1 small	3.4	2.0***	1.1	1.1	1.4	−2.0	−0.6
2	3.1	2.5	−0.6	1.6	1.9	−1.3	−0.7
3	25.3	26.3**	2.0	−0.9	3.4	−22.0	−22.9*
4	18.4	15.9	28.6*	22.6**	61.9**	43.5	46.0
5 large	144.3*	211.5***	52.6	−34.8	−170.5	−314.8**	−382.1***

$Turnover\,quintiles_{j,q-1}$, fund size quintiles $Fund\,size\,quintiles_{j,q-1}$, and stock-cap quintiles $Stock\text{-}cap\,quintiles_{j,q-1}$ as independent variables. We use subscripts $q-1$ and $y-1$ to denote the one-quarter and one-year lagged variables, respectively. Fund size quintiles are sorted based on their TNAs at the end of each quarter, and stock-cap quintiles are based on their average stock-cap quintiles of all holdings as assigned in Daniel et al. (1997) at the end of each quarter. We control for the one-quarter lagged expense ratio ($Exp\,ratio_{j,q-1}$) in percentage, fund age ($Age_{j,q-1}$), quarterly fund flow ($Flow_{j,q-1}$) as a fraction of fund TNAs, and past-year fund return ($Ret\,pastly_{j,y-1}$) in the regression. We also include day fixed effects υ_t. Summary statistics for all variables used in the regression analysis are reported in Table I, Panel B,

We estimate the fund flow of each mutual fund j in quarter q as

$$Flow_{j,q} = \frac{TNA_{j,q} - TNA_{j,q-1} * (1 + R_{j,q})}{TNA_{j,q-1}(1 + R_{j,q})}, \tag{32}$$

where $TNA_{j,q}$ is the TNAs for each fund j at the end of quarter q in the CRSP mutual fund database, and $R_{j,q}$ is the quarterly return of fund j during quarter q. If a fund's $TNA_{j,q}$ is zero, its fund flow $Flow_{j,q}$ is -100%.

As Prediction 1 predicts, we find that funds' value added from holdings shorter than 1 to 20 days are significantly positively correlated with fund turnover quintiles, whereas funds' value added from holdings longer than 240 days are significantly negatively correlated with fund turnover quintiles (as reported in Table VI). Funds' value added from holdings shorter than 10 days increases with fund size quintiles as predicted in equation (16) and Berk and van Binsbergen (2015). Moreover, we find that value added shorter than five days decreases with stock-cap quintiles, indicating that funds' short-term value added comes mainly from small-cap stocks rather than large-cap stocks. This result is consistent with the finding in Barras, Gagliardini, and Scaillet (2022) that small-cap funds on average have higher value added than large-cap funds.

B. Value Added of High-Turnover Funds on FOMC and Earnings Announcement Days

To characterize the sources of high-turnover funds' short-term value added, we investigate FOMC meeting days, earnings announcement days, and M&A announcement days for value added from holdings shorter than 40 days.[37] We count the three days around each announcement (i.e., $[-1, 1]$) as event days. As reported in Table VII, high-turnover funds' holdings shorter than two weeks (10 days) add as much as 1.6 million dollars per year on FOMC announcement days and 1.3 million dollars on earnings announcement days, which account for 46.8% and 38.3%, respectively, of the 3.3 million dollar total value added from holdings shorter than two weeks. Since there are some overlaps between FOMC announcement and earnings announcement days, high-turnover funds' holdings shorter than two weeks (10 days) add 2.7 million dollars per year on these two types of announcement days together, which accounts for 82.4%, not 85.1% (= 46.8% + 38.3%), of their total value added from

[37] We obtain FOMC days from the Federal Reserve website (http://www.federalreserve.gov), earning announcements days from the Compustat, and U.S. domestic M&A announcement days from Zephyr.

Table VI

Regression Analysis of Value Added on Fund Turnover by Holding Periods

This table reports regression results of value added from holdings shorter (longer) than 20 (240) days on one-quarter lagged turnover quintiles. We sorted funds into turnover quintiles according to their total turnover including both purchases and sales every quarter, fund size quintiles based on their TNAs at the end of each quarter, and stock-cap quintiles based on their average stock-cap quintiles of all holdings as assigned in Daniel et al. (1997) at the end of each quarter. *VA n* corresponds to value added of holdings shorter than n (1 to 20) days, and *VA 240+* to value added from holdings longer than 240 days. We control for one-quarter lagged fund size quintiles, stock-cap quintiles, expense ratio (*Exp ratio*) in percentage, fund age (*Age*), quarterly fund flow (*Flow*), and past-year fund return (*Ret pastly*) in the regressions. Value added is annualized and in million dollars. Day fixed effects are included. Robust standard errors are clustered at the day level. Significance level: ***0.01, **0.05, and *0.1.

	VA 1 (1)	*VA 2* (2)	*VA 5* (3)	*VA 10* (4)	*VA 20* (5)	*VA 240+* (6)
L.Turnover quintiles	0.839***	0.812***	1.040***	1.379**	1.485*	−31.423***
	(5.18)	(4.01)	(3.17)	(2.57)	(1.78)	(−2.95)
L.Fund size quintiles	1.154***	1.139***	1.306***	1.378**	1.445	7.170
	(6.35)	(4.85)	(3.43)	(2.24)	(1.46)	(0.74)
L.Stock-cap quintiles	−0.307***	−0.399***	−0.507**	−0.458	−0.590	−7.624
	(−2.83)	(−2.61)	(−2.12)	(−1.20)	(−0.99)	(−1.09)
L.Exp ratio	0.386	0.407	0.186	−0.521	−0.357	−48.676
	(1.06)	(0.90)	(0.27)	(−0.50)	(−0.24)	(−1.59)
L.Age	0.021	0.004	−0.004	0.069	0.127	−0.158
	(0.75)	(0.10)	(−0.06)	(0.72)	(0.81)	(−0.13)
L.Flow	0.382	1.215	4.486**	6.689**	12.209**	131.483**
	(0.39)	(0.91)	(2.12)	(2.06)	(2.24)	(2.02)
Ret pastly	1.161	2.019	4.587	0.175	0.620	20.563
	(0.65)	(0.80)	(1.05)	(0.02)	(0.05)	(0.05)
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	131,964	131,964	131,964	131,964	131,964	94,133
Adjusted R^2	0.012	0.012	0.018	0.023	0.025	0.066

holdings shorter than two weeks. This fraction is large considering that FOMC meeting days represent only about 9.5% (3 event days $\times$ 8 meetings = 24 days out of 253 trading days) of all trading days and earnings announcement days represent 4.7% ($3\times4=12$ out of 253). This finding is consistent with informed institutional trading before earnings and FOMC announcements documented in the literature. For example, Campbell, Ramadorai, and Schwartz (2009) and Hendershott, Livdan, and Schürhoff (2015) find that institutional order flow before earnings announcements is more positive before positive earnings shocks, and Bernile, Hu, and Tang (2016) document informed trading during news embargoes ahead of FOMC announcements in the direction of subsequent policy surprises.

The fractions of value added earned on FOMC and earnings announcement days increase within two weeks and decrease substantially after a month (20 days), indicating that the purchases are mostly made within a month before

Table VII
Short-Term Value Added of High-Turnover Funds on FOMC, Earnings, and M&A Announcement Days

This table reports the value added of high-turnover (Q5) funds' short-term holdings from FOMC meeting days, earnings announcement days, and M&A announcement days per year. We consider the three days around each announcement (i.e., [−1, 1]). Day 0 corresponds to new purchases on the same day. Panel A reports the value added per year in million dollars, and Panel B reports the value added as a percentage of value added from all trading days per year. Value added of high-turnover (Q5) funds from all trading days is reported in Panel A of Table IV; we repeat it in the last column of this table for comparison. Robust standard errors are clustered at the day level. Significance level: ***0.01, **0.05, and *0.1.

	Event Days [−1, 1]			
Day	FOMC	Earnings	M&A	All Days
Panel A: Value Added of Net Purchases (in million dollars)				
0	0.1	0.3***	−0.0	1.4***
1	0.5*	0.4***	0.0	2.6***
2	0.7**	0.4**	0.1	2.3***
5	1.2***	0.6*	0.2	2.9***
10	1.6***	1.3***	0.2	3.3**
20	1.7*	1.9***	0.9**	4.2*
30	1.4	1.9**	1.4***	6.4*
40	1.2	2.3**	1.8***	6.6*
Panel B: As a Percent of Value Added from All Trading Days				
0	7.3	20.0***	−0.5	–
1	18.9*	14.7***	1.2	–
2	31.8**	15.2**	3.5	–
5	41.2***	18.9*	5.6	–
10	46.8***	38.3***	5.4	–
20	39.6*	45.3***	20.2**	–
30	22.4	28.9**	22.1***	–
40	18.2	34.3**	26.9***	–

these announcements. For low-turnover funds' holdings longer than a year, only 21.0% of their value added is earned on FOMC announcement days, with this effect statistically insignificant. Since both FOMC and earnings announcements are scheduled in advance, high-turnover funds can build up their positions in a relatively short period of time leading up to these announcements. In contrast, M&A announcements are not scheduled in advance. We find that high-turnover funds add value on M&A announcement days through their holdings longer than two weeks, indicating that they build up their positions at least two weeks in advance.

C. Price Impact Costs by Fund Turnover and Fund Size

Our model predicts that, because funds investing in short-term opportunities cannot spread their trades over time to the same degree as funds investing in long-term opportunities, price impact costs are higher for the former per dollar of investment (Corollary 1). In particular, equation (18) of our model predicts that controlling for fund size, there is a positive correlation between fund turnover and price impact costs.

C.1. Double-Sorting by Fund Turnover and Fund Size Quintiles

To test this prediction, we double-sort funds by fund size and turnover to control for the effect of fund size.

Table VIII reports the price impact costs of purchases and sales measured by execution shortfalls in Panels A and B (as defined in equation (29)) as a percentage of dollar trading amounts. Consistent with the prediction above, the execution shortfalls of purchases for high-turnover funds (turnover quintile 5) are 13.8 to 56.0 bps higher than low-turnover funds (turnover quintile 1) controlling for fund size (as reported in Panel A). These numbers are both economically and statistically significant for all fund size quintiles. Similarly, the execution shortfalls of sales for high-turnover funds (turnover quintile 5) are 12.0 to 57.9 bps higher than those for low-turnover funds (turnover quintile 1) (as reported in Panel B). These results are consistent with the ticket-level analysis in Busse et al. (2021), which shows that fund turnover remains a significant determinant after controlling for both fund-level and ticket-level characteristics, such as fund size, investment style, ticket size, stock liquidity, and volatility. Moreover, the significantly negative execution shortfall of large low-turnover funds (−29.7 bps for funds in fund size quintile 5 and turnover quintile 1) suggests that they actually profit from providing liquidity to other investors during the execution of their trades.

Panel C of Table VIII reports price impact costs by fund turnover quintiles only. Consistent with Prediction 2, the execution shortfall of purchases increases from −18.5 bps for low-turnover funds (quintile 1) to 23.6 bps for high-turnover funds (quintile 5), with the difference of 42.1 bps both economically and statistically significant. The execution shortfall of sales shows a similar trend.

Lastly, Panel D of Table VIII shows that the price impact costs measured by execution shortfalls are hump-shaped in fund size without controlling for fund turnover, which is consistent with the prediction in Proposition 2 that, in equilibrium, the magnitude of price impact costs depends only on the fund's alpha opportunity instead of its size or turnover. This is because the optimal amount of capital invested q_h^* is determined by the fund's horizon-specific skill (value added), which takes fund turnover and price impact costs b_h into account. This hump-shaped relation between fund size and price impact costs is consistent with the empirical evidence of Busse et al. (2021), who find that larger funds trade less frequently and hold bigger stocks to actively avoid incurring higher trading costs. While they focus on the interaction of fund size and stock liquidity, we emphasize the interaction of fund size and investment horizon as a potential explanation of this hump-shaped relation.

Table VIII

Price Impact Costs Double-Sorted by Fund Turnover and Fund Size Quintiles

This table reports the price impact costs of trades for 25 portfolios double-sorted by fund turnover and fund size. We sort funds into turnover quintiles according to their total turnover including both purchases and sales every quarter, and fund size quintiles based on their TNAs at the end of last quarter. We then construct 25 portfolios based on the intersections of these fund turnover and size quintiles. We measure price impact costs by the execution shortfalls of trades, which constitute the price changes from the placement of the order to the execution of the trade divided by the price at the placement of the order (as shown in equation (29)). Panels A and B report the average execution shortfalls of purchases and sales separately. Panel C reports the execution shortfalls of trades sorted by fund turnover quintiles only, and Panel D reports results sorted by fund size quintiles only. All numbers in this table are reported in bps of trading amounts in dollars, value-weighted across trades in each fund-day, and equally weighted across fund-day observations. Robust standard errors are clustered at both the day and the fund levels. Significance level: ***0.01, **0.05, and *0.1.

(in bps of Trading Amounts)	Turnover Quintile					
Fund Size Quintiles	1 Low	2	3	4	5 High	(5−1)
Panel A: Execution Shortfalls of Purchases						
1 small	−4.4	7.4	4.7	−6.7	22.7***	27.1**
2	0.7	3.8	5.1	10.7	27.4***	26.7***
3	4.8	7.3	1.4	6.2	18.6***	13.8*
4	−27.9**	0.8	−9.0	3.2	28.1***	56.0***
5 large	−29.7***	−6.3*	−1.2	11.8**	21.8***	51.6***
Panel B: Execution Shortfalls of Sales						
1 small	4.3	13.1**	13.5*	4.3	25.3***	21.0*
2	13.1	6.5	11.2	17.7*	35.9***	22.8**
3	12.3	20.7***	5.4	17.2***	24.4***	12.0
4	−18.1**	6.7	−3.6	10.0*	39.8***	57.9***
5 large	−23.2***	−2.6	−0.8	11.5*	21.1***	44.3***

Panel C: By Turnover Quintiles Only

	Turnover Quintiles					
(in bps of Trading Amounts)	1 low	2	3	4	5 high	(5−1)
Purchases	−18.5***	1.1	−1.2	5.7	23.6***	42.1***
Sales	−9.4*	6.9**	3.0	12.4***	29.7***	39.1***

Panel D: By Fund Size Quintiles Only

	Fund Size Quintiles					
(in bps of Trading Amounts)	1 small	2	3	4	5 large	(5−1)
Purchases	8.5*	13.5***	9.5**	1.4	−5.4	−13.9**
Sales	15.2***	20.8***	17.4***	9.7*	−2.5	−17.7***

Table IX

Regression Analysis of Execution Shortfalls on Fund Turnover and Size

This table reports regression results of execution shortfalls on one-quarter lagged turnover quintiles. We sort funds into turnover quintiles according to their total turnover including both purchases and sales every quarter, fund size quintiles based on their TNAs at the end of each quarter, and stock-cap quintiles based on their average stock-cap quintiles of all holdings as assigned in Daniel et al. (1997) at the end of each quarter. *ES all*/*buy*/*sell* corresponds to execution shortfalls of all trades/purchases/sales. We control for one-quarter lagged fund size quintiles, stock-cap quintiles, expense ratio (*Exp ratio*) in percentage, fund age (*Age*), quarterly fund flow (*Flow*), and past year fund return (*Ret pastly*) in the regressions. Execution shortfalls are measured in bps of trading amounts. Day fixed effects are included. Robust standard errors are clustered at both the day and the fund levels. Significance level: ***0.01, **0.05, and *0.1.

	ES all (1)	*ES buy* (2)	*ES sell* (3)
L.Turnover quintiles	8.083***	7.580***	7.297***
	(4.93)	(4.39)	(5.09)
L.Fund size quintiles	−2.605	−2.600*	−2.864*
	(−1.63)	(−1.66)	(−1.73)
L.Stock-cap quintiles	−0.862	−0.740	−0.740
	(−0.52)	(−0.44)	(−0.48)
L.Exp ratio	16.369***	13.687***	14.507***
	(2.89)	(2.64)	(2.82)
L.Age	0.416**	0.444**	0.261
	(2.19)	(2.16)	(1.55)
L.Flow	14.553	8.356	13.151
	(1.06)	(0.63)	(0.93)
Ret pastly	−48.381**	−33.172	−49.408***
	(−2.54)	(−1.63)	(−2.62)
Day fixed effects	Yes	Yes	Yes
Observations	83,320	68,349	67,092
Adjusted R^2	0.032	0.127	0.112

C.2. Regression Analysis of Price Impact Costs

We also test our model predictions on price impact costs using regression analysis in which we control for other fund characteristics. We replace the dependent variable in equation (31) by *ES all*, *ES buy*, and *ES sell* for execution shortfalls of all trades, purchases, and sales, respectively, at the fund-day level. All execution shortfalls of trades are averaged per fund-day and value-weighted by trading dollar amounts. As reported in columns (1), (2), and (3) of Table IX, the execution shortfalls of both purchases and sales increase significantly with fund turnover quintiles, and the t-statistics on the coefficients of turnover (4.39 to 5.09) are highest for all of the independent variables, suggesting that fund turnover is one of the most important determinants of execution shortfalls. These large t-statistics of fund turnover are consistent with the fund-level regressions of Busse et al. (2021).

D. Alpha Opportunities before Price Impact Costs

Next, we investigate Prediction 3, which states that the short-term holdings of high-turnover funds have higher stock alphas before price impact costs than the short-term holdings of low-turnover funds. In this section, we focus on the alpha opportunities that high-turnover and low-turnover funds profit from before price impact costs (corresponding to the α_S and α_L in our model at different horizons), instead of the net value added after price impact costs. Specifically, we calculate the stock alphas of funds' net purchases (holdings) before price impact costs as a percentage of total trading amount, rather than in dollar amounts (as the case for value added) or as a percentage of fund TNAs (as the case for the contribution to fund gross alphas). We find that the alpha opportunities captured by high-turnover funds shortly after their trades are substantially larger than those captured by low-turnover funds, and they diminish quickly in the following year. These results confirm that high- and low-turnover funds profit from different sources of alpha opportunities, consistent with our finding in the previous sections that the short-term value added of high-turnover funds is mainly earned on FOMC and earnings announcement days, whereas the long-term value added of low-turnover funds comes largely from their exposure to the value factor.

D.1. Analysis by Fund Turnover Quintiles

Table X reports the daily alphas (before price impact costs) captured by net purchases within the past 240 days by fund turnover quintile. We compute these alphas by dividing the value added of net purchases in equation (28) plus the price impact costs of purchases (measured by the execution shortfall in dollar as in equations (29) and (30)) by the total dollar amount of net purchases. We find that stocks purchased by high-turnover funds (quintile 5) on the same day (day 0) have an average daily alpha of 40.2 bps before price impact costs, and stocks purchased within 1/2/5 days have a daily alpha of 26.1/19.9/12.4 bps before price impact costs. These numbers are statistically significant at the 1% significance level. This daily alpha declines to 4.0 bps for purchases within 40 days and stays at the same level until 240 days. In contrast, stocks purchased by low-turnover funds on average have negative alpha on the same day and alpha of 5.2 bps at most for holdings shorter than 240 days.

Panel B of Table X tests the difference between high-turnover (Q5) funds and low-turnover (Q1) funds. Under both the original measure based on α_h and the new measure based on order statistics, the differences are significant at the 95% confidence level for holdings shorter than 240 days in all 18 cases, and at the 99% confidence level in 13 out of 14 cases for holdings shorter than 60 days.

D.2. Regression Analysis of Alpha Opportunities

Since the choice of investment horizon depends not only on the magnitude of alpha opportunities but also on the scale of investment ideas, it is important

Table X

Alphas Opportunities before Costs: Low-Turnover Funds versus High-Turnover Funds

This table reports alpha opportunities before price impact costs (α_S and α_L in our model) captured by funds' net purchases in the past 240 days by turnover quintile. Day 0 is for purchases on the same day. Funds are sorted into turnover quintiles according to their total turnover including both purchases and sales every quarter. Quintile 1 is for low-turnover funds and quintile 5 is for high-turnover funds. The daily alphas captured by the net purchases in the past n (0 to 240) days is calculated as the daily value added of net purchases in equation (28) plus the price impact costs of purchases in dollars measured by the execution shortfall (as in equations (29) and (30)), divided by the total dollar amount of purchases. Panel A reports daily alphas by turnover quintile. Panel B reports the average differences in daily alphas between quintiles 5 and 1, and their associated p-values. The differences are averaged across days. We also report the fraction of days that high-turnover funds (quintile 5) have a higher α_h than low-turnover funds (quintile 1) and their associated p-values. All p-values are one-tailed, that is, they represent the probability of the observed test statistic value being greater, under the null hypothesis that the daily alpha of high-turnover funds is equal to or less than that of low-turnover funds. Daily alphas are reported in bps of trading amounts in dollars, value-weighted across trades in each fund-day, and equally weighted across fund-day observations. The CAPM is used as the benchmark model. Robust standard errors are clustered at the day level. Significance level: ***0.01, **0.05, and *0.1.

Panel A: Alphas before Price Impact by Turnover Quintile

Daily Alphas (in bps)	Turnover Quintile				
Day	1 Low	2	3	4	5 High
0	−1.9	27.7***	23.7***	24.4***	40.2***
1	2.7	19.2***	15.8***	17.5***	26.1***
2	5.2***	14.5***	12.1***	12.7***	19.9***
5	5.2***	10.5***	8.8***	9.6***	12.4***
10	3.4***	7.1***	6.4***	6.1***	8.5***
20	2.1**	4.2***	5.2***	2.8***	5.4***
40	1.2	3.5***	3.3***	2.3***	4.0***
60	1.4	3.4***	2.2***	1.7**	3.6***
120	1.1	2.3***	1.6**	1.8***	3.5***
240	1.8**	2.3***	1.6**	1.8**	4.0***

Panel B: Differences in Daily Alphas before Price Impact (α_h)

	α_h (5−1)		Prob (5 > 1)	
Daily Alphas (in bps)	in bps	p-Value (%)	Freq. (%)	p-Value (%)
1	23.4***	0.00	58.27***	0.00
2	14.7***	0.00	55.42***	0.00
5	7.2***	0.00	54.68***	0.00
10	5.1***	0.05	53.49***	0.00
20	3.3***	0.35	52.64***	0.25
40	2.8***	0.55	52.21***	1.00
60	2.2**	1.15	52.75***	0.20
120	2.4***	0.95	52.61***	0.30
240	2.2**	2.60	51.57**	4.95

to control for the scale of the fund's investments while studying the relation between short-term alpha and fund turnover.[38] We use the log dollar amount of holdings shorter than n days, ln*(Holdings n days)*, as a measure of the scale of their short-term investments. In particular, we replace the dependent variable in Reg. 31 by *Alpha n* for alphas before price impact costs of holdings shorter than n (1 to 20) days, and we include the log dollar amount of holdings shorter than n days, ln*(Holdings n days)*, as a control for the scale of the investment. As Prediction 3 states, alphas of holdings shorter than 1 to 10 days increase with fund turnover quintiles and the coefficients are statistically significant (reported in Table XI). Furthermore, we find that short-term alphas are substantially larger for investments in small-cap stocks than large-cap stocks, consistent with larger price inefficiencies in small-cap stocks compared to large-cap stocks. In the next section, we uncover the determinants of funds' decreasing returns-to-scale parameters using transaction data and investigate the importance of parameter λ to funds' decreasing returns to scale, which subsequently affects their choices of investment horizon.

E. Uncovering the Determinants of Decreasing Returns to Scale

In our baseline model, we assume the parameter for price impact cost λ to be a constant regardless of investment opportunities to focus on the heterogeneity of decreasing returns to scale b_h related to the investment horizon T_h. As shown in equation (15), however, a fund's choice of investment horizon may also depend on λ if it differs across horizons and funds (e.g., Anand et al. (2012), Pástor, Stambaugh, and Taylor (2020), and Harvey et al. (2021)). In this subsection, we allow the price impact cost parameter to depend on the fund-specific investment horizon, denoted by λ_h. We then assess the extent to which λ_h is associated with other variables, such as stock liquidity, number of investment ideas, and trade execution skill. This change also allows us to quantify the contributions of the investment horizon T_h and other determinants of price impact costs to funds' decreasing returns to scale b_h.

Replacing the parameter for price impact cost λ in equation (10) by a horizon-specific price impact cost λ_h gives

$$b_h \equiv \frac{\lambda_h}{2(1-\beta^{T_h})\Gamma_h}, \tag{33}$$

in which a fund's decreasing returns to scale b_h depends on both its price impact cost parameter λ_h and investment horizon T_h. Substituting equation (33) into equation (15) gives

$$\hat{J}_h^* = \frac{a_h^2}{2\lambda_h}(1-\beta^{T_h})\Gamma_h. \tag{34}$$

[38] The scale of investment ideas is an important determinant of the price impact cost parameter λ in equation (15), which we discuss in detail in Section IV.E. Equation (15) shows that the value added of short- and long-term investing $\hat{J}_h^*$ depends not only on the magnitude of alpha opportunities a_h but also on λ.

Table XI

Regression Analysis of Alphas on Fund Turnover by Holding Period

This table reports regression results of short-term alpha opportunities before price impact costs (α_S) captured by holdings shorter than 20 days on one-quarter lagged turnover quintiles. We sort funds into turnover quintiles according to their total turnover including both purchases and sales every quarter, fund size quintiles based on their TNAs at the end of each quarter, and stock-cap quintiles based on their average stock-cap quintiles of all holdings as assigned in Daniel et al. (1997) at the end of each quarter. *Alpha n* corresponds to the alpha of holdings shorter than n (1 to 20) days. We control one-quarter lagged fund size quintiles, stock-cap quintiles, expense ratio (*Exp ratio*) in percentage, fund age (*Age*), quarterly fund flow (*Flow*), and past-year fund return (*L.Ret*) in the regressions. ln(*Holdings n days*) is the log dollar amount of holdings shorter than n days. Alpha is in bps per day. Day fixed effects are included. Robust standard errors are clustered at the day level. Significance level: ***0.01, **0.05, and *0.1.

	Alpha 1 (1)	*Alpha 2* (2)	*Alpha 5* (3)	*Alpha 10* (4)	*Alpha 20* (5)
L.Turnover quintiles	2.860***	1.094**	0.815**	0.885**	0.213
	(5.21)	(2.25)	(2.04)	(2.54)	(0.75)
L.Fund size quintiles	−0.049	−0.346	0.094	0.115	−0.572
	(−0.07)	(−0.56)	(0.18)	(0.25)	(−1.43)
L.Stock-cap quintiles	−4.302***	−3.574***	−2.278***	−1.521***	−0.995***
	(−8.16)	(−7.39)	(−5.48)	(−3.99)	(−2.86)
L.Exp ratio	9.883***	5.683***	1.276	−0.953	−1.545*
	(6.39)	(4.17)	(1.14)	(−0.98)	(−1.95)
L.Age	0.198***	0.104*	0.089**	0.094**	0.084***
	(3.16)	(1.89)	(1.99)	(2.54)	(2.82)
L.Flow	−0.678	3.214	2.335	6.725**	2.798
	(−0.13)	(0.69)	(0.62)	(2.19)	(1.10)
Ret pastly	−9.474	−6.437	0.062	1.720	3.709
	(−0.99)	(−0.76)	(0.01)	(0.28)	(0.73)
ln(*Holdings n days*)	−0.557	−0.350	−0.935**	−0.965***	−0.419
	(−1.15)	(−0.78)	(−2.35)	(−2.60)	(−1.25)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	82,473	91,011	105,183	115,681	123,192
Adjusted R^2	0.050	0.042	0.043	0.048	0.059

Equation (34) shows that, in addition to the alpha opportunity a_h and the investment horizon T_h, the value added of a fund $\hat{J}_h^*$ also depends on the price impact cost parameter λ_h, indicating that a fund may choose a high-turnover strategy because of a smaller price impact cost parameter λ_S for short-term investing (as in Proposition 1). Therefore, our model further predicts a negative correlation between the price impact cost parameter λ_h and fund turnover, holding all else equal.

As the model predicts, we find that high-turnover funds' λ_S is substantially smaller than that of low-turnover funds at the fund level, indicating that λ_h affects funds' choice of investment horizon. Evidence suggests that the smaller λ_S of high-turnover funds comes from a larger scale of short-term investment ideas, as opposed to better trade execution skill or more liquid stock holdings. The difference in short-term skills between high- and medium- turnover funds

Table XII

Price Impact Costs and Decreasing Returns-to-Scale Parameters by Turnover Quintile

This table reports estimated values of price impact cost parameter λ_h and decreasing returns-to-scale parameter b_h in equation (33) by turnover quintile. Funds are sorted into turnover quintiles according to their total turnover including both purchases and sales every quarter. Q1 is for low-turnover funds and Q5 is for high-turnover funds. As in our value-added analysis, we use daily price impact costs and trading amounts of each fund for this estimation. In Panel A, we estimate λ_h by regressing the percentage price impact cost of purchases per fund-day ($PI_h = \lambda_h q_h / 2\Gamma_h$ from equation (6) on the dollar amount of purchases on that day q_h/Γ_h (in million dollars), which is *after the fund's spreading of total trading amounts over time* (as in Lemma 1). We control for fund fixed effects and day fixed effects in this regression. The percentage price impact cost PI_h is empirically measured as the value-weighted execution shortfall of purchases as in Panel C of Table VIII. In Panel B, we estimate b_S using the estimates of λ_h in Panel A and investment horizon T_h. For simplicity, we consider a one-shot investment problem with no discounting, in which case equation (33) becomes $b_h = \lambda_h / 2T_h$ because $\Gamma_h = T_h$. We define T_h as the inverse of fund turnover for each quintile. Robust standard errors are clustered per day. Significance level: ***0.01, **0.05, and *0.1.

(bps/million dollars)	Turnover Quintile					
Day	1 Low	2	3	4	5 High	(5−1)
	Panel A: Price Impact Cost Parameter λ_h					
λ_h	0.848***	0.709**	0.281**	0.273**	0.122***	−0.726**
	(2.74)	(2.18)	(2.17)	(2.19)	(4.80)	(−2.08)
	Panel B: Decreasing Returns-to-Scale Parameter $b_h = \lambda_h * Turnover/2$					
b_h	0.123***	0.276**	0.191**	0.325**	0.490***	0.367***
	(2.74)	(2.18)	(2.17)	(2.19)	(4.80)	(3.14)

(turnover quintiles 2 to 5) are driven largely by λ_h, instead of alpha a_h, supporting the view that value added is a better measure of short-term skill than alpha alone. Moreover, we compare the contributions of λ_h and T_h (the spreading of trades over time) to the variation in decreasing returns to scale b_h across turnover quintiles, and we find that the effect of T_h dominates.

Table XII reports the estimated values of the price impact cost parameter λ_h and the degree of decreasing returns to scale b_h in equation (33) by turnover quintile. As in our value-added analysis, we use daily price impact costs and trading amounts of each fund for this empirical estimation. In Panel A, we estimate λ_h by regressing the percentage price impact costs of purchases per fund-day ($PI_h = \lambda_h q_h / 2\Gamma_h$ from equation (6) on the dollar amount of purchases on that day q_h/Γ_h (in million dollars), which is *after the fund's spreading of total trading amounts over time* (as in Lemma 1).[39] We control for fund fixed

[39] We use price impact costs of purchases for this estimation to be consistent with our measure of value added by holding periods, where we document that the effect of sales on the daily value added of a fund is negligible. Using the price impact costs of both purchases and sales for this estimation gives similar results.

effects and day fixed effects in this regression. The percentage price impact costs PI_h are empirically measured by the value-weighted execution shortfalls of purchases as in Panel C of Table VIII. In Panel B, we estimate b_S using the estimates of λ_h in Panel A and investment horizon T_h. For simplicity, we consider a one-shot investment problem with no discounting, in which case equation (33) becomes $b_h = \lambda_h/2T_h$ because $\Gamma_h = T_h$. We measure T_h as the inverse of fund turnover for each quintile.

We find in Panel A that λ_h decreases monotonically with turnover quintiles, with the λ_h of high-turnover funds in quintile 5 significantly smaller than the λ_h in quintiles 1 to 4, indicating that the price impact costs of high-turnover funds increase less with their daily trading amounts than those of low-turnover funds. This finding supports our model prediction that funds that are better at scaling up their short-term opportunities (a smaller λ_S in equation (34)) are more likely to choose high-turnover strategies. However, after accounting for the effect of the investment horizon T_h (the spreading of trades over time), the realized decreasing returns-to-scale parameter b_S becomes largely increasing with turnover quintiles, and hence b_S is significantly larger for high-turnover funds in quintile 5 compared to funds in quintiles 1 to 4. This result shows that the contribution of the investment horizon T_h to the decreasing returns to scale b_h dominates that of λ_h across turnover quintiles, which confirms Corollary 1 in our model. Our estimates of b_h are close to Barras, Gagliardini, and Scaillet (2022). Using fund returns, these authors document a decreasing returns-to-scale parameter for high-turnover funds (tercile 3) about double the size of that for low-turnover funds (tercile 1).

As discussed in Section I, a smaller λ_S can be caused by the higher liquidity of the stocks traded (e.g., Pástor, Stambaugh, and Taylor (2020)), a larger number of investment ideas (e.g., Harvey et al. (2021)), or superior trade execution skill (e.g., Anand et al. (2012)). To further pin down the sources of high-turnover funds' smaller price impact cost parameter λ_S at the fund level, in Table XIII we report the average market capitalization of stock holdings, number of stocks, and trade execution skill by turnover quintile and holding period.

For stock liquidity, we find in Table XIII, Panel A that the average market capitalization (liquidity) of stocks held largely decreases with fund turnover quintile. For holdings shorter than 5 to 20 days, stocks held by high-turnover funds (quintile 5) have significantly smaller market capitalization (i.e., are less liquid) than stocks held by funds with lower turnover (quintiles 1 to 4).[40] Therefore, the smaller price impact cost parameter λ_S of high-turnover funds is *not* related to trading more liquid stocks. High-turnover funds invest more in small-cap stocks that are less liquid arguably because small-cap stocks provide more short-term alpha opportunities than large-cap stocks do. It is worth noting that this finding is not in conflict with the finding in Pástor, Stambaugh, and Taylor (2020) that high-turnover funds on average have higher portfolio liquidity, since their measure of portfolio liquidity also

[40] The results are similar when we use Amihud's ILLIQ measure or stocks' size quintiles for this analysis.

Table XIII

Stock Market Capitalization, Number of Stocks, and Trade Execution Skill by Turnover Quintile

This table reports the average market capitalization of stock holdings, number of stocks, and trade execution skill by turnover quintile. Funds are sorted into turnover quintiles according to their total turnover including both purchases and sales every quarter. Quintile 1 is for low-turnover funds and quintile 5 is for high-turnover funds. Panel A reports the value-weighted market capitalization of stock holdings shorter than n days (1 to 60). Day 0 is for new purchases on the same day. The last row reports the market capitalization of all stock holdings. Market capitalization values are reported in billion dollars. Panel B reports the average number of stock holdings shorter than n days (1 to 60). The last row reports the average total number of stocks holdings in the fund's portfolio. The last column in Panels A and B reports the difference between quintiles 5 and 1, and robust standard errors are clustered per quarter. In Panel C, we estimate the fund's trade execution skill measures $\tilde{a}$ and $\tilde{\lambda}$ by regressing the percentage price impact costs of trades per fund-stock-day on the dollar amount of net purchases (in million dollars) controlling for stock and day fixed effects. Parameter $\tilde{a}$ is the intercept and $\tilde{\lambda}$ is the slope of this regression. Robust standard errors are clustered by fund, stock, and day in Panel C. Significance level: ***0.01, **0.05, and *0.1.

	Turnover Quintile					
Day	1 Low	2	3	4	5 High	(5−1)
Panel A: Market Capitalization (in billion dollars, Average per Fund-Day)						
0	21.9	20.7	20.0	19.3	20.0	−1.9
1	23.8	23.4	22.1	21.4	21.1	−2.7**
2	24.7	24.6	23.1	22.4	21.7	−3.0**
5	26.4	26.6	24.6	23.9	22.8	−3.7***
10	27.5	27.9	25.9	24.7	23.5	−4.0***
20	28.0	29.0	26.6	25.4	24.0	−4.0***
40	29.1	29.7	27.9	26.5	25.6	−3.5**
60	29.8	30.5	29.2	27.6	26.9	−2.9*
All holdings	39.8	37.5	35.7	37.5	30.1	−9.7***
Panel B: Number of Stocks (Average per Fund-Day)						
0	6.8	4.6	6.3	6.4	14.4	7.7***
1	9.0	6.0	8.3	8.9	18.9	9.8***
2	10.8	7.2	9.9	11.1	22.3	11.5***
5	14.8	9.9	13.5	16.1	29.7	14.9***
10	19.5	13.2	18.1	22.5	38.0	18.6***
20	26.3	17.6	24.7	31.2	48.0	21.7***
40	34.8	23.0	32.2	39.8	55.6	20.8***
60	39.5	25.5	35.2	41.5	54.7	15.2**
All holdings	194.8	96.8	103.1	109.2	91.4	−103.4***
Panel C: Trade Execution Skill (in bps/million dollars, Estimated per Fund-Stock-Day)						
$\tilde{\lambda}$	−0.414	0.256	0.195	1.000**	1.571***	1.984**
	(−0.69)	(1.08)	(0.45)	(2.15)	(6.18)	(2.56)
$\tilde{a}$	−5.0***	−0.8	−0.1	2.3	15.6***	20.6***
	(−3.33)	(−0.77)	(−0.07)	(0.96)	(12.26)	(4.98)

increases with the number of stocks in the portfolio. That is, the average trading amount in each stock will be smaller if a larger number of stocks are traded.

Consistent with this logic, we find in Panel B of Table XIII that high-turnover funds (quintile 5) invest in substantially more stocks in the short-term (<40 days) than do funds with lower turnover (quintiles 1 to 4). For holdings shorter than 20 days, the number of stocks invested in by high-turnover funds in quintile 5 is about three times the number of stocks invested in by funds in quintile 2. This result suggests that the smaller λ_S of high-turnover funds is due at least in part to a larger number of short-term investment ideas, which echoes the finding in Harvey et al. (2021) that the number of investment ideas is an important determinant of funds' decreasing returns to scale.

Moreover, we test the trade execution skill of high- versus lower-turnover funds by comparing their execution shortfalls of trading individual stocks. In Panel C of Table XIII, we estimate the fund's trade execution skill measures $\tilde{\alpha}$ and $\tilde{\lambda}$ by regressing the percentage price impact costs of trades per fund-stock-day on the dollar amount of net purchases (in million dollars) controlling for stock and day fixed effects. The parameter $\tilde{\alpha}$ denotes the intercept, which is used in Anand et al. (2012) as a measure of the trading desk's trade execution skill, and $\tilde{\lambda}$ is the slope of this regression, which measures the increase in execution shortfall for a one million dollar increase in trading amount on an average stock. Both measures should be lower for funds with higher trade execution skill. However, we find that both $\tilde{\alpha}$ and $\tilde{\lambda}$ are substantially higher for high- than low-turnover funds, indicating that the trade execution skill of high-turnover funds is lower. Therefore, the smaller price impact cost parameter λ_S of high-turnover funds is not caused by better trade execution skill.

Overall, our results suggest that high-turnover funds' larger number of short-term investment ideas more than reverse their disadvantages introduced by relatively worse trade execution skill and trading less liquid stocks, leading to a smaller price impact cost parameter λ_S at the fund level.

F. Value Added of Holdings Using Monthly Holdings Data

Finally, we run the same value-added decomposition using monthly holdings data for the sample of 2,492 U.S. equity mutual funds over the period 1993 to 2020 from Morningstar to show that our results can be generalized to a larger sample of mutual funds. As reported in Table XIV, and consistent with our previous analyses, high-turnover (Q5) funds' holdings shorter than one to three months add 3.0 to 3.9 million dollars per year, which is consistently higher than the value added of low-turnover (Q1) funds and funds in other quintiles (Q2 to Q4), whereas the value added of low-turnover (Q1) funds from holdings longer than 12 months is substantially larger than that of high-turnover (Q5) funds and funds in other quintiles, equal to a significantly positive 12.4 million dollars per year. These results based on monthly holdings confirm that our findings can be generalized to a larger sample of U.S. equity mutual funds. However, compared with the results based on daily holdings and transactions in Table IV, the value added from holdings shorter than one month (20 days) are

Table XIV

Value Added by Investment Horizon and Fund Turnover using Monthly Holdings

This table reports the value added from holdings shorter than (net purchases in the past) 12 months by turnover quintile using the monthly holdings data of 2,492 U.S. equity funds from Morningstar. The sample time period is from 1993 to 2020. We sort funds into turnover quintiles according to their annual turnover reported in CRSP. Quintile 1 is for low-turnover funds and quintile 5 is for high-turnover funds. Panel A reports the value added from net purchases in the past n (1 to 12) months, which is calculated using equation (28) for monthly CAPM abnormal returns (CAPM). The value added of all holdings (i.e., the value added of a fund) is also reported in the "All holdings" row, and ">12" is the value added from holdings that have been in the portfolio longer than 12 months. Panel B reports t-statistics. Value added is equally weighted across fund-day observations, annualized, and reported in million dollars. Robust standard errors are clustered at the month level. Significance level: ***0.01, **0.05, and *0.1.

	Turnover Quintile				
Month	1 Low	2	3	4	5 High
Panel A: Value Added of Net Purchases (in million dollars)					
1	0.5	−1.8	0.6	−0.8	3.0
2	0.5	−3.1*	0.3	−0.9	3.4
3	0.4	−3.4*	0.5	−1.0	3.9*
4	0.0	−3.1	0.4	−1.6	1.5
5	−0.2	−3.6	0.0	−1.0	3.5
6	−0.1	−3.2	−0.4	−1.4	3.2
7	0.2	−3.7	0.4	−1.3	2.6
8	0.2	−4.0	0.3	−1.5	3.9
9	0.2	−4.3	0.7	−1.4	3.0
10	0.0	−4.6	0.3	−1.7	3.3
11	0.3	−4.7	0.9	−1.7	3.5
12	0.2	−5.1*	0.6	−1.7	3.1
>12	12.4**	7.9*	2.9	−2.5	−1.0
All holdings	12.6*	2.8	3.5	−4.3	2.2
Panel B: t-Statistics					
1	0.80	−1.09	0.63	−0.69	1.62
2	0.62	−1.70	0.29	−0.70	1.63
3	0.38	−1.71	0.40	−0.66	1.72
4	0.02	−1.45	0.26	−0.97	0.79
5	−0.14	−1.60	0.01	−0.53	1.29
6	−0.10	−1.34	−0.22	−0.69	1.13
7	0.10	−1.45	0.18	−0.57	0.96
8	0.10	−1.52	0.15	−0.62	1.20
9	0.10	−1.57	0.27	−0.57	0.88
10	0.02	−1.63	0.13	−0.66	0.93
11	0.11	−1.59	0.35	−0.61	0.97
12	0.09	−1.68	0.23	−0.59	0.84
>12	2.45	1.65	0.98	−1.36	−0.64
All holdings	1.80	0.44	0.73	−1.01	0.45

smaller and insignificantly different from zero for funds in turnover quintiles 2 to 5. There are two straightforward explanations for these somewhat weaker results. First, the analysis using monthly holdings neglects all intraday trading profits of a fund (Day 0 in Table IV), which can be as large as 0.6 to 1.4 million dollars per year for funds in Q2 to Q5 after accounting for the large execution shortfalls of trades on the same day. Second, the monthly analysis neglects all of the short-term trading profits realized before the end of each month, which represents a large fraction of the 0.8 to 3.3 million dollars of value added within 10 days (Day 10 in Table IV) for funds in Q2 to Q5. Although the short-term value added of high-turnover (Q5) funds is underestimated for these two reasons, their 3.9 million dollars value added within three months is significantly positive under the 90% confidence interval, and the t-statistic of their 3.0 million dollars value added within one month is as high as 1.62, suggesting once again that high-turnover funds do possess short-term trading skill.

Besides neglecting all trading profits realized before month-end, the analysis using monthly holdings has other drawbacks compared with using transaction and daily holdings data. We summarize three such drawbacks here using the results of high-turnover funds in Q5 as an example. First, without transaction data (i.e., actual execution prices), we cannot determine whether the 3.0 million dollar value added of high-turnover funds within a month is large enough to cover their large price impact costs of trades. Second, not knowing when exactly the position is established or closed in a month introduces measurement error in the estimated value added within a month. For example, if a position is established on the second day of a month and closed on the second day the next month, using the monthly return of the next month to calculate the value added of this new holding within a month is incorrect. Third, we do not know whether this 3.0 million dollar value added from holdings shorter than a month is from very short-term holdings (i.e., within one day or one week) or from holdings beyond two weeks. Our decomposition based on daily holdings (in Table III) shows that, of the 4.2 million dollar value added from holdings within a month (20 days), 3.3 is from holdings within two weeks (10 days), 2.9 is within a week (5 days), and 1.4 is earned on the same day. Moreover, all interim trades established and closed within a month are not captured by monthly holdings.

V. Conclusion

In this study, we propose a motivating model in which funds specialize at different investment horizons, and they choose their fund turnover based on their horizon-specific skills and the price impact of their trades. As the model predicts, our empirical decomposition shows that holdings of high-turnover funds shorter than two weeks add a substantial amount of value mainly on FOMC and earnings announcement days, whereas holdings of low-turnover funds only add value at longer horizons.

Future research could further investigate the determinants of funds' horizon-specific skills, such as the investment horizons of their investors, the risk-aversion levels of their fund managers, and the investment styles of other funds in the same fund family. Another interesting direction would be to investigate the determinants of low-turnover funds' decreasing returns to scale, for which the price impact costs play a lesser role. Moreover, given our analysis focuses on mutual funds that are mostly long-term investors, conducting similar analysis for shorter-term investors such as hedge funds and high-frequency traders could shed further light on the horizon-related trade-offs that investment managers face.

Initial submission: March 4, 2021; Accepted: February 1, 2022
Editors: Stefan Nagel, Philip Bond, Amit Seru, and Wei Xiong

Appendix

A. Proofs in Section I

PROOF OF LEMMA 1: Because the last term $\beta^{T_h-1}\big(E[R_h]q_h+\beta J\big)$ in equation (2) is unaffected by the fund's choice, we can convert the maximization problem into the minimization problem

$$\min_{(w_1,w_2,\ldots,w_{T_h})\in\mathcal{W}} \sum_{\tau=1}^{T_h}\beta^{\tau-1}C(w_\tau). \tag{A1}$$

Because the nonnegativity constraint never binds, the Lagrangian of the problem is given by

$$\mathcal{L}=\sum_{\tau=1}^{T_h}\beta^{\tau-1}C(w_\tau)+\eta\left(q_h-\sum_{\tau=1}^{T_h}w_\tau\right).$$

The first-order condition is then given by

$$w_\tau=\beta^{-(\tau-1)}\frac{\eta}{a}\text{ for all }\tau=1,2,..,T_h, \tag{A2}$$

and

$$\sum_{\tau=1}^{T_h}w_\tau=q_h. \tag{A3}$$

Summing equation (A2) over all τ yields

$$\sum_{\tau=1}^{T_h}w_\tau=\frac{\eta}{a}\Gamma_h. \tag{A4}$$

By substituting equation (A3) into equation (A4) and solving for η, we have

$$\eta = \frac{aq_h}{\Gamma_h}. \tag{A5}$$

Substituting equation (A5) into equation (A2) gives equation (5), from which equation (6) is immediate. □

PROOF OF PROPOSITION 1: We first denote the present value of trading profits for investment opportunity h by Π_h:

$$\Pi_h \equiv -\frac{bq_h^2}{2\Gamma_h} + \beta^{T_h - 1}\alpha_h q_h. \tag{A6}$$

We claim that $J_S > J_L$ if and only if $\hat{J}_S > \hat{J}_L$. We first prove the "only if" part. Suppose that $J_S > J_L$. Because $J \equiv \max(J_S, J_L) = J_S$, we have

$$J_S = \Pi_S + \beta^{T_S} J = \Pi_S + \beta^{T_S} J_S, \tag{A7}$$

which implies $J_S = \hat{J}_S = \frac{\Pi_S}{1-\beta^{T_S}}$. We then have

$$\hat{J}_S = J_S > J_L = \Pi_L + \beta^{T_L} J \geq \Pi_L + \beta^{T_L} J_L \geq \hat{J}_L. \tag{A8}$$

We prove the "if" part. Suppose that $\hat{J}_S > \hat{J}_L$. Then

$$J \geq \hat{J}_S > \frac{\Pi_L}{1-\beta^{T_L}}, \tag{A9}$$

which implies

$$J > \Pi_L + \beta^{T_L} J = J_L. \tag{A10}$$

Because $J \equiv \max(J_S, J_L)$, it has to be the case that $J = J_S$, which implies $J_S > J_L$. This finishes the proof of the claim. □

Finally, because q_h can be any given number in the proof above for both q_S and q_L, the claim is still true for endogenous q_h^*. Therefore, the fund chooses S over L if and only if $\hat{J}_S^* \geq \hat{J}_L^*$.

B. Generalization with Partial Indexing

In this section, we generalize our model by allowing the fund to invest part of its capital in the passive benchmark (i.e., indexing) as in Berk and Green (2004). Assuming that investment opportunity h is optimal for the fund, we denote by q the TNAs of the fund that includes both actively managed capital q_h and capital invested in the index q_I. As is shown in Section I, $f^* = a_h/2$ is the optimal fee if the fund only raises capital for active management. If we allow passive investing, it is optimal for the fund to choose any fee f less than or equal to f^*. The optimal strategy for the manager is to put q_h^* into active management and index the difference, $q - q_h^* = q_I$.

Dividing equation (15) by q gives the gross alpha of the fund that chooses strategy h,

$$\alpha^g(q) = \frac{a_h^2}{4b_h q}. \tag{B1}$$

As shown in equation (B1), the fund's gross alpha decreases with the increase in fund size even if the fund's alpha opportunity a_h and price impact costs b_h do not change, corroborating that gross alpha is not a consistent measure across fund size.

Rearranging equation (14) using equation (B1) gives the equilibrium size of the fund as a function of fee f,

$$q = \frac{a_h^2}{4fb_h} = \frac{\hat{J}_h^*}{f}. \tag{B2}$$

Therefore, the equilibrium fund size is determined by the fund's skill (value added $\hat{J}_h^*$) together with the fee. Since skilled funds may specialize in either the short term or long term, the correlation between fund size and the horizon that the fund specializes in is ambiguous. Fixing the skill of the fund shows a one-to-one relation between the fee f and fund size q. Fixing the fee, the fund size increases with the fund's alpha opportunity a_h and decreases with the price impact of trades b_h.[41]

Relaxing the fee f of our model allows us to explore the interactions among fund characteristics such as fund size, fees, turnover, and price impact costs. To see this, substituting equation (18) into a_h in equation (B2) yields

$$PI = \sqrt{qfb_h}, \tag{B3}$$

which suggests that although the price impact costs depend only on the fund's alpha opportunity in equilibrium, equation (B3) predicts a positive correlation between the fund's realized price impact costs and these three fund characteristics after controlling for the other two. This prediction is consistent with Pástor, Stambaugh, and Taylor (2020), except that we focus on the realized price impact costs of a fund and its interaction with the fund's turnover, instead of the fund's portfolio liquidity.

More importantly, Proposition 2 shows that the latent factor that drives all these correlations with price impact costs is the fund's horizon-specific alpha opportunity a_h. The equilibrium price impact costs are higher for high-turnover funds than low-turnover funds, even without controlling for fund size and fee. Since fund size is a function of the fund's value added, which depends on both a_h and b_h (equation (B2)), the correlation between fund size and price

[41] Without the price impact of trades ($b_h = 0$), any fund with a positive a_h attracts an infinite amount of capital from investors, which is unsustainable. Thus, the price impact of trades has to be positive and increasing with the trading amount.

Table A1

Holdings by the Past Length of Holding Periods (As a Fraction of Total Holdings)

This table reports holdings by the past length of holding periods as a fraction of total holdings. Panel A reports results for all funds. Panel B reports results by fund category. Holdings shorter than (net purchases within) 20 to 240 days and holdings longer than 240 days are reported as a fraction of total holdings. All numbers are value-weighted by fund TNAs.

Panel A: All Funds

	All Funds
<20 days	0.03
<60 days	0.07
<120 days	0.10
<240 days	0.13
>240 days	0.87

Panel B: By Fund Categories

Turnover Quintile	1 Low	2	3	4	5 High
<20 days	0.01	0.03	0.05	0.07	0.21
<60 days	0.03	0.07	0.12	0.16	0.43
<240 days	0.08	0.12	0.18	0.19	0.60
>240 days	0.92	0.88	0.82	0.81	0.40
Fund Size Quintile	1 Small	2	3	4	5 Large
<20 days	0.06	0.08	0.07	0.06	0.02
<60 days	0.14	0.17	0.14	0.14	0.06
<240 days	0.17	0.18	0.18	0.21	0.11
>240 days	0.83	0.82	0.82	0.79	0.89

impact costs, or the correlation between fund size and the horizon over which value is added, are ambiguous without controlling for fund turnover.

REFERENCES

Alexander, Gordon J., Gjergji Cici, and Scott Gibson, 2007, Does motivation matter when assessing trade performance? An analysis of mutual funds, *Review of Financial Studies* 20, 125–150.

Anand, Amber, Paul Irvine, Andy Puckett, and Kumar Venkataraman, 2012, Performance of institutional trading desks: An analysis of persistence in trading costs, *Review of Financial Studies* 25, 557–598.

Back, Kerry, and Shmuel Baruch, 2004, Information in securities markets: Kyle meets Glosten and Milgrom, *Econometrica* 72, 433–465.

Barber, Brad M., Xing Huang, and Terrance Odean, 2016, Which factors matter to investors? Evidence from mutual fund flows, *Review of Financial Studies* 29, 2600–2642.

Barras, Laurent, Patrick Gagliardini, and Olivier Scaillet, 2022, Skill, scale, and value creation in the mutual fund industry, *Journal of Finance* 77, 601–638.

Berk, Jonathan B., and Richard C. Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

Berk, Jonathan B., and Jules H. van Binsbergen, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* 118, 1–20.

Berk, Jonathan B., and Jules H. van Binsbergen, 2016, Assessing asset pricing models using revealed preference, *Journal of Financial Economics* 119, 1–23.

Berk, Jonathan B., and Jules H. van Binsbergen, 2017, Mutual funds in equilibrium, *Annual Review of Financial Economics* 9, 147–167.

Bernile, Gennaro, Jianfeng Hu, and Yuehua Tang, 2016, Can information be locked up? Informed trading ahead of macro-news announcements, *Journal of Financial Economics* 121, 496–520.

Bikker, Jacob A., Laura Spierdijk, and Pieter Jelle van der Sluis, 2007, Market impact costs of institutional equity trades, *Journal of International Money and Finance* 26, 974–1000.

Briere, Marie, Charles-Albert Lehalle, Tamara Nefedova, and Amine Raboun, 2019, Stock market liquidity and the trading costs of asset pricing anomalies, Université Paris-Dauphine Research Paper.

Bushee, Brian J., 1998, The influence of institutional investors on myopic R&D investment behavior, *Accounting Review* 73, 305–333.

Bushee, Brian J., 2001, Do institutional investors prefer near-term earnings over long-run value?, *Contemporary Accounting Research* 18, 207–246.

Bushee, Brian J., and Christopher F. Noe, 2000, Corporate disclosure practices, institutional investors, and stock return volatility, *Journal of Accounting Research* 38, 171–202.

Busse, Jeffrey A., Tarun Chordia, Lei Jiang, and Yuehua Tang, 2021, Transaction costs, portfolio characteristics, and mutual fund performance, *Management Science* 67, 1227–1248.

Busse, Jeffrey A., Lin Tong, Qing Tong, and Zhe Zhang, 2019, Trading regularity and fund performance, *Review of Financial Studies* 32, 374–422.

Caldentey, René, and Ennio Stacchetti, 2010, Insider trading with a random deadline, *Econometrica* 78, 245–283.

Campbell, John Y., Tarun Ramadorai, and Allie Schwartz, 2009, Caught on tape: Institutional trading, stock returns, and earnings announcements, *Journal of Financial Economics* 92, 66–91.

Cella, Cristina, Andrew Ellul, and Mariassunta Giannetti, 2013, Investors' horizons and the amplification of market shocks, *Review of Financial Studies* 26, 1607–1648.

Chakrabarty, Bidisha, Pamela C. Moulton, and Charles Trzcinka, 2017, The performance of short-term institutional trades, *Journal of Financial and Quantitative Analysis* 52, 1403–1428.

Chan, Louis K. C., and Josef Lakonishok, 1997, Institutional equity trading costs: NYSE versus Nasdaq, *Journal of Finance* 52, 713–735.

Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers, 2000, The value of active mutual fund management: An examination of the stockholdings and trades of fund managers, *Journal of Financial and Quantitative Analysis* 35, 343–368.

Chen, Joseph, Harrison Hong, Ming Huang, and Jeffrey D. Kubik, 2004, Does fund size erode mutual fund performance? The role of liquidity and organization, *American Economic Review* 94, 1276–1302.

Cohen, Randolph B., Joshua D. Coval, and L'uboš Pástor, 2005, Judging fund managers by the company they keep, *Journal of Finance* 60, 1057–1096.

Conrad, Jennifer, and Gautam Kaul, 1998, An anatomy of trading strategies, *Review of Financial Studies* 11, 489–519.

Çötelioğlu, Efe, Francesco Franzoni, and Alberto Plazzi, 2021, What constrains liquidity provision? Evidence from institutional trades, *Review of Finance* 25, 485–517.

Cremers, K. J. Martijn, and Antti Petajisto, 2009, How active is your fund manager? A new measure that predicts performance, *Review of Financial Studies* 22, 3329–3365.

Cremers, Martijn, and Ankur Pareek, 2015, Short-term trading and stock return anomalies: Momentum, reversal, and share issuance, *Review of Finance* 19, 1649–1701.

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

Crouzet, Nicolas, Ian Dew-Becker, and Charles G. Nathanson, 2020, On the effects of restricting short-term investment, *Review of Financial Studies* 33, 1–43.

Da, Zhi, Pengjie Gao, and Ravi Jagannathan, 2011, Impatient trading, liquidity provision, and stock selection by mutual funds, *Review of Financial Studies* 24, 675–720.
Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.
Di Mascio, Rick, Anton Lines, and Narayan Y. Naik, 2017, Alpha decay and institutional trading, Available at SSRN 2580551.
Dong, Xi, Shu Feng, and Ronnie Sadka, 2019, Liquidity risk and mutual fund performance, *Management Science* 65, 1020–1041.
Dong, Xi, and Massimo Massa, 2013, Excess autocorrelation and mutual fund performance, AFA 2014 Philadelphia Meetings Paper.
Dow, James, Jungsuk Han, and Francesco Sangiorgi, 2021, Hysteresis in price efficiency and the economics of slow-moving capital, *Review of Financial Studies* 34, 2857–2909.
Edelen, Roger M., Richard B. Evans, and Gregory B. Kadlec, 2007, Scale effects in mutual fund performance: The role of trading costs, Available at SSRN 951367.
Frazzini, Andrea, Ronen Israel, and Tobias J. Moskowitz, 2012, Trading costs of asset pricing anomalies, Fama-Miller Working Paper, Chicago Booth Research Paper.
Gârleanu, Nicolae, and Lasse Heje Pedersen, 2013, Dynamic trading with predictable returns and transaction costs, *Journal of Finance* 68, 2309–2340.
Gaspar, José-Miguel, Massimo Massa, and Pedro Matos, 2005, Shareholder investment horizons and the market for corporate control, *Journal of Financial Economics* 76, 135–165.
Harvey, Campbell R., Yan Liu, Eric K. M. Tan, and Min Zhu, 2021, Crowding: Evidence from fund managerial structure, Available at SSRN 3554636.
Hendershott, Terrence, Dmitry Livdan, and Norman Schürhoff, 2015, Are institutions informed about news?, *Journal of Financial Economics* 117, 249–287.
Jame, Russell, 2018, Liquidity provision and the cross section of hedge fund returns, *Management Science* 64, 3288–3312.
Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2014, Time-varying fund manager skill, *Journal of Finance* 69, 1455–1484.
Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2005, On the industry concentration of actively managed equity mutual funds, *Journal of Finance* 60, 1983–2011.
Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2008, Unobserved actions of mutual funds, *Review of Financial Studies* 21, 2379–2416.
Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2016, A rational theory of mutual funds' attention allocation, *Econometrica* 84, 571–626.
Keim, Donald B., 1999, An analysis of mutual fund design: The case of investing in small-cap stocks, *Journal of Financial Economics* 51, 173–194.
Keim, Donald B., and Ananth Madhavan, 1996, The upstairs market for large-block transactions: Analysis and measurement of price effects, *Review of Financial Studies* 9, 1–36.
Keim, Donald B., and Ananth Madhavan, 1997, Transactions costs and investment style: An interexchange analysis of institutional equity trades, *Journal of Financial Economics* 46, 265–292.
Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315–1335.
Lan, Chunhua, Fabio Moneta, and Russ Wermers, 2023, Holding horizon: A new measure of active investment management, *Journal of Financial and Quantitative Analysis*, 1–45. https://doi.org/10.1017/s0022109023000303
Pástor, L'uboš, Robert F. Stambaugh, and Lucian A. Taylor, 2017, Do funds make more when they trade more?, *Journal of Finance* 72, 1483–1528.
Pástor, L'uboš, Robert F. Stambaugh, and Lucian A. Taylor, 2020, Fund tradeoffs, *Journal of Financial Economics* 138, 614–634.
Patton, Andrew J., and Brian M. Weller, 2020, What you see is not what you get: The costs of trading market anomalies, *Journal of Financial Economics* 137, 515–549.
Pollet, Joshua M., and Mungo Wilson, 2008, How does size affect mutual fund behavior?, *Journal of Finance* 63, 2941–2969.
Pool, Veronika K., Noah Stoffman, and Scott E. Yonker, 2012, No place like home: Familiarity in mutual fund manager portfolio choice, *Review of Financial Studies* 25, 2563–2599.

Pool, Veronika K., Noah Stoffman, and Scott E. Yonker, 2015, The people in your neighborhood: Social interactions and mutual fund portfolios, *Journal of Finance* 70, 2679–2732.

Puckett, Andy, and Xuemin Yan, 2011, The interim trading skills of institutional investors, *Journal of Finance* 66, 601–633.

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2009, Information immobility and the home bias puzzle, *Journal of Finance* 64, 1187–1215.

von Beschwitz, Bastian, Sandro Lunghi, and Daniel Schmidt, 2022, Fundamental arbitrage under the microscope: Evidence from detailed hedge fund transaction data, *Review of Asset Pricing Studies* 12, 199–242.

Wermers, Russ, 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses, *Journal of Finance* 55, 1655–1695.

Wermers, Russ, Tong Yao, and Jane Zhao, 2012, Forecasting stock returns through an efficient aggregation of mutual fund holdings, *Review of Financial Studies* 25, 3490–3529.

Yan, Xuemin, and Zhe Zhang, 2009, Institutional investors and equity returns: Are short-term institutions better informed?, *Review of Financial Studies* 22, 893–924.

Yan, Xuemin Sterling, 2008, Liquidity, investment style, and the relation between fund size and fund performance, *Journal of Financial and Quantitative Analysis* 43, 741–767.

Zhu, Min, 2018, Informative fund size, managerial skill, and investor rationality, *Journal of Financial Economics* 130, 114–134.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.