A Horizon-Based Decomposition of Mutual Fund Value Added using Transactions *

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Abstract

We propose a model featuring horizon-specific mutual fund manager skill. Managers optimally choose their holdings based on their skill and the price impact of their trades. Fund turnover negatively correlates with the horizon over which value is added and positively correlates with price impact costs, while the correlation with fund size is ambiguous. We empirically evaluate the model using transaction-level data and decompose funds' value added based on the past length of funds' holdings. Holdings of high-turnover funds add a substantial amount of value in the first two months, while holdings of low-turnover funds only add value over longer horizons.

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1 Introduction

The objective of active mutual funds is to find investments that add value over and above their investors' alternative investment opportunity set. However, the way funds go about achieving this objective exhibits large cross-sectional variation in the data, particularly when it comes to the average holding period of their 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 ten times per year.[1] An important question is whether the large observed differences in fund turnover result from funds possessing skills (adding value) at different investment horizons, or from funds trading too much (or too little) destroying value in the process. This remains an open question in the mutual fund literature mainly because of the anonymity of transaction-level data. In this study, we propose a model where funds specialize at different investment horizons, and they choose their holdings based on their horizon-specific skills and the price impact of their trades. The model provides empirically testable predictions of the correlation between fund turnover and the horizon over which value is added, as well as their correlations with price impact costs. We then evaluate the model's predictions using transaction-level data and decompose funds' value added based on the past length of their holdings.

The main insight of our model is that a fund chooses its investment horizon (fund turnover) based on its horizon-specific skill (value added), while optimally taking into account the associated price impact costs. Through this price impact channel our model endogenously introduces heterogeneity in decreasing returns to scale at the fund level (Berk and van Binsbergen [2015] and Zhu [2018]).[2] Funds investing in short-term opportunities cannot spread their trades over time as much as funds investing in long-term opportunities can, implying 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 (1) the gross alpha before price impact costs (or decreasing returns to scale) are taken into account, (2) the price impact costs (or scalability of the strategy), and (3) the fact that multiple short-term investments can be deployed in the time span as one long-term investment.

Our study 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, a country, or an industry, it is likely to continue this investment in information acquisition and build up its comparative advantage in that area. Crouzet, Dew-Becker,

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

[2] For more studies on the decreasing returns to scale at the fund-level see Pollet and Wilson (2008), Yan (2008), Pastor, Stambaugh, and Taylor (2020), and Barras, Gagliardini, and Scaillet (2020).

and Nathanson (2020) further show that investors build horizon-specific skills endogenously for similar reasons. Building on these insights, we formulate an infinite-horizon trading model with price impact where a fund has horizon-specific skill.

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, the fund turnover contains information about its horizon-specific skills. Specifically, our model predicts that there is a negative correlation between fund turnover and the horizon over which the value is added. That is, high-turnover funds add more value through their short-term holdings and low-turnover funds add more value through their long-term holdings.

To test the model's prediction, 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 with the quarterly holdings data in the Thomson Reuters database from 1999 to 2010 (using the method in Busse, Chordia, Jiang, and Tang [2020]) and the mutual fund data (including fund characteristics) from the Center for Research in Security Prices (CRSP). Using these data, we identify 332 U.S. mutual funds and construct a unique dataset of their daily holdings. These detailed transaction data set 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. In particular, we decompose a fund's daily holdings into short- and long-term holdings (holdings shorter and longer than n days) based on the past length of holding periods, and we compute the fund's daily value added from short- and long-term holdings separately.

As predicted by the model, our empirical decomposition shows markedly different results depending on fund turnover: for high-turnover funds, the holdings (net purchases) shorter than two months 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 and confirm the model's prediction that there is a positive (negative) correlation between turnover and short-term (long-term) value added. Consistent with this logic, we also find that short-term value added of high-turnover funds result largely from their exposures to the momentum factor, and long-term value added of low-turnover funds result largely from their exposures to the value factor.

We formally test the difference in value added between low-turnover funds and high-turnover funds at different horizons using order statistics. The results confirm that high-turnover funds have a higher value added than low-turnover funds from holdings shorter than two months, and low-turnover funds have a higher value added than high-turnover funds from holdings longer than a year. These results hold at the 95% confidence level. Moreover, we confirm that the alphas (before price impact costs) of stocks bought by high-turnover funds are substantially higher than those of low-turnover funds within a year, as our model predicts. 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 [2020]).[3]

Our model also predicts a positive correlation between fund turnover and price impact costs (both before and after controlling for fund size) because funds cannot spread their trades over time much when investing in short-term investment opportunities. Meanwhile, it predicts that the price impact costs increase more with fund size for high-turnover funds than for low-turnover funds. To test these predictions, we double-sort funds into 25 portfolios based on both their turnover and size, and calculate the average price impact costs measured by the execution shortfall of trades for each portfolio. This double-sorting analysis confirms the positive correlation between fund turnover and price impact costs, as well as the higher correlation between fund size and price impact costs for high-turnover funds than for low-turnover funds. 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.

There is a large empirical literature investigating the relations between fund size, price impact costs, as well as fund performance (e.g., Pollet and Wilson [2008], Yan [2008], Busse, Chordia, Jiang, and Tang [2020], and Pastor, Stambaugh, and Taylor [2020]).[4] The results of this literature are mixed, which is consistent with our model's prediction that the correlation between fund size, price impact costs, and fund gross alpha are ambiguous (before controlling for fund turnover). Pastor, Stambaugh, and Taylor (2020), as well as other scholars, document that funds adapt their investment strategies to their fund sizes and the price impact of trades by trading more liquid stocks, diversify their portfolios more, and trade less frequently. Complementing these results, we find that funds' investors have already taken horizon-specific skill and price impact costs into account when allocating their capital. Specifically, our model shows that fund size, turnover, and fund gross alpha

[3]Barras, Gagliardini, and Scaillet (2020) 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 (DRS) between gross alpha and size. Value added (the product of size and gross alpha) simply measures the end result in dollars.

[4]Also refer to the large corpus of literature on decreasing returns to scale at the fund-level, including Berk and Green (2004), Chen, Hong, Huang, and Kubik (2004), Zhu (2018), and Barras, Gagliardini, and Scaillet (2020).

are endogenously decided by the fund's horizon-specific skill (value added) and fee in a rational expectations equilibrium where investors chase any investment opportunity with positive net alpha, and the price impact of trades is a function of only the fund's alpha opportunity before price impact costs.[5]

Our decomposition approach contributes to 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 the trades of each fund.[6] Cremers and Pareek (2016) and Lan, Moneta, and Wermers (2019) construct direct measures for the average investment horizon of a fund and find using alpha measures that long-horizon funds outperform short-horizon funds in the cross-section. However, different trades of one fund usually target profits at different horizons.[7] 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-term and long-term investment opportunities; our decomposition method allows for different horizons for different trades 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.[8] 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 a better long-term performance as illustrated in our model.

Recently, there has been an increased focus in the mutual fund literature on holdings and transactions. On one hand, a large thread of literature uses quarterly holdings data to explore, using alpha measures, whether or which fund managers outperform.[9] Although quarterly holdings are useful, they are only infrequent snapshots of funds' portfolios and neglect the short-term effect of

[5]This result holds assuming that the fund sets a fee sufficiently low to attract enough capital for its active strategies as in Berk and Green (2004).

[6]Studies using fund turnover and churn ratio as measures of the average investment horizon of a fund include Gaspar, Massa, and Matos (2005), Carhart (1997), Bushee (1998, 2000, 2001), Yan and Zhang (2009), Cella, Ellul, and Giannetti (2013), and Pastor, Stambaugh, and Taylor (2017). Most studies use quarterly holdings data to construct their horizon measures.

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

[8]See, for example, Chen, Jegadeesh, and Wermers (2000), Yan and Zhang (2009), Puckett and Yan (2011), Chakrabarty, Moulton, and Trzcinka (2017), and Busse, Tong, Tong, and Zhang (2018).

[9]This thread of literature includes Daniel, Grinblatt, Titman, and Wermers (1997), Wermers (2000), Kasperczyk, Sialm, and Zheng (2005), Cohen, Coval, and Pastor (2005), Cremers and Petajisto (2009), Da, Gao, and Jagannathan (2010), Dong and Massa (2013), Cremers and Pareek (2015), Kacperczyk, van Nieuwerburgh, and Veldkamp (2014) (2016), and Dong, Feng, and Sadka (2017). Another thread uses the 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 (2006), Wermers, Yao, and Zhao (2012), Lan, Moneta, and Wermers (2019).

trades on fund performance. To capture this short-term effect, Kasperczyk, Sialm, and Zheng (2008) measure the impact of intra-quarter 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.[10] Because of the anonymity of institutional investors, these articles could not link the analysis to long-term holdings and compare the contribution of trades across different horizons. Further, the differences in the data used by the quarterly holding literature and the transaction literature can lead to discrepancies. For example, the former uses actual holdings, whereas the later uses hypothetical holdings inferred from transactions and assumptions on their investment horizon. In this study, we close this gap by merging transaction data with the quarterly holdings data and designing a method to measure all the open positions' impact on a fund's value added by the past length of holding periods.

This study also relates to the trading cost literature, which estimates trading costs from transaction data (e.g., Chan and Lakonishok [1997], Keim and Madhaven [1996, 1997], and Bikker, Spierdijk, and van der Sluis [2007]). Moreover, the liquidity provision of low-turnover funds documented in this study compliments studies investigating the relationship between the liquidity provision of trades, fund performance, and stock liquidity (e.g., Keim [1999], Jame [2017], and Cotelioglu, Franzoni, and Plazzi [2020]).

2 Model

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 the trading gains relative to investors' alternative investment opportunity set.

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

[10] For example, Campbell, Ramadorai, and Schwartz (2009) infer daily institutional trades from the Transactions and Quotes (TAQ) database and 13-F 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 intra-quarter and that interim trading skill is persistent. Jame (2017) documents that hedge funds who provide liquidity outperform; and Busse, Tong, Tong, and Zhang (2018) find that institutional investors who 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.

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 (1) finds new short-term and long-term investment opportunities; (2) chooses either of the two opportunities;[11] and (3) chooses the amount of capital, q_h, to invest in this opportunity and reallocate the capital from the old investment to the new one.[12] 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 quadratic price impact costs of changing positions in the dollar amount of w_t from an existing investment to an new investment is given by:

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

where b is a positive constant. This is equivalent to a linear relation between the trading amount and the price impact costs expressed as a percentage.[13] Economically, b can differ across stocks and portfolios in term of liquidity (e.g., Zhu [2018]), and across funds in term of trading skill (e.g., Anand, Irvine, Puckett, and Venkataraman [2012] and Frazzini, Israel, and Moskowitz [2012]). Since we focus on the importance of differing investment horizons in this study, we shut down the heterogeneity of b across stocks and funds for simplicity. Instead, our model generates endogenous differences in price impact costs across short- and long- term opportunities. 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 $\mathrm{E}[R_h]q_h$ and the continuation value J less price impact costs $C(w_\tau)$:

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

[11] 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. 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 the portfolio weights: instead of choosing the opportunity that the fund specializes in, the fund tilts its portfolio towards the opportunities where it specializes.

[12] Later, we will 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.

[13] The quadratic cost function is assumed only for simplicity of analysis, and our results are not affected qualitatively by the alternative assumption of a general convex cost function.

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

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

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

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

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*

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

and the present value of price impact costs is given by

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

where

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

Proof. See Section A.3 in Appendix. □

Lemma 1 is in line with standard trading models with price impact in the literature, such as Kyle (1985). To see more clearly, consider the limit case where $\beta \to 1$, where there is no discount over time. Then, Eq. (5) implies that the fund trades an equal amount every period, that is, $w_\tau^* = q_h/T_h$.

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 Eq. (6) into Eq. (2) yields

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

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.[14] That is, solving Eq. (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:

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

The first term of Eq. (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 Eq. (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 Eq. (8) by q_h gives us the gross alpha (the alpha before fees but after price impact costs) of a fund that chooses strategy h and invests all its capital in this strategy as

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

Our expressions for value added in Eq. (8) and gross alpha in Eq. (12) are closely related to those of gross alpha (Berk and Green [2004]) and 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 Eq. (8) with respect to q_h equal to zero, we

[14] See, for example, Dow, Han and Sangiorgi (2020) for further discussions.

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. Substituting Eq. (13) into Eq. (8) gives the maximum present value of value added when the fund chooses strategy h as

$$\hat{J}_h^* = \frac{a_h^2}{4b_h}. \tag{14}$$

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:*

$$\hat{J}_S^* = \frac{a_S^2}{4b_S} > \frac{a_L^2}{4b_L} = \hat{J}_L^*. \tag{15}$$

Proof. See Section A.3 in Appendix. □

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. *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 ($\hat{J}_S^* > \hat{J}_L^*$), Eq. (15) should be true. This implies

$$a_S > a_L\sqrt{\frac{b_S}{b_L}} > a_L \tag{16}$$

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

$$a_L > a_S\sqrt{\frac{b_L}{b_S}}, \tag{17}$$

which gives the desired result. □

The 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 either because of its higher long-term alpha before price impact costs or because of its cost advantage in case of investing for a longer term.

The fund can always opt to invest a part of its capital in the passive benchmark (i.e., indexing). We denote q as the total net assets (TNAs) of the fund that includes both actively-managed capital q_h and capital invested in the index q_I. Dividing Eq. (14) by q gives the gross alpha of the fund that chooses strategy h as

$$\alpha^g(q) = \frac{a_h^2}{4b_h q}. \tag{18}$$

As shown in Eq. (18), the fund's gross alpha decreases with the increase of fund size even if the fund's alpha opportunity a_h and price impact costs b_h do not change. Therefore, gross alpha is not a consistent measure across fund size.

We now turn to investors and assume that they have rational expectations, as in Berk and Green (2004) and Berk and van Binsbergen (2015, 2017). A rational investor will chase any investment opportunity with positive NPV. This implies that all assets earn an expected return commensurate with the risk of the asset. Then, all funds must have net alphas of zero:

$$\alpha^n(q) \equiv \alpha^g(q) - f = \frac{a_h^2}{4b_h q} - f = 0. \tag{19}$$

If the fund picks its fee, f, equal to

$$f^* = \frac{a_h}{2}, \tag{20}$$

investors will choose to invest $q_h^* = a_h/2b_h$ into the fund, and the fund will invest all the capital q_h^* into opportunity h. As a consequence, the fund's net alpha will be zero and the market will be in equilibrium. The gross alpha becomes $\alpha^g = f^* = \frac{a_h}{2}$. As in Berk and van Binsbergen (2017), it is optimal for the fund to choose any fee f below, or equal to f^* to raise enough capital for investing in opportunity h. The optimal strategy for the manager is to put q_h^* into active management and index the difference, $q - q_h^* = q_I$. Rearranging Eq. (19) and using the expression of optimal value added in Eq. (14) give the equilibrium size of the fund as a function of fee f as

$$q = \frac{a_h^2}{4fb_h} = \frac{\hat{J}_h^*}{f}. \tag{21}$$

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 short- 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 the 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.[15]

Proposition 3. *The present value of equilibrium price impact costs as a percentage of total trading amounts can be represented as a function of only the fund's alpha opportunity, that is,*

$$PI_h = b_h q_h^* = \frac{a_h}{2}. \tag{22}$$

Proof. The second term of Eq. (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 Eq. (13) gives $b_h q_h^* = a_h/2$. □

Proposition 3 gives a rather striking result that, in equilibrium, the magnitude of price impact costs only depends 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 the 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.

Eq. (22) 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 ($b_S > b_L$). Eq. (22) further shows that, when the fund invests an optimal amount of capital ($q_h = q_h^*$), the price impact costs are also higher for a fund investing in short-term opportunity because of Proposition 2 ($a_S > a_L$). In addition, Eq. (22) predicts that the price impact costs increase with q_h more for high-turnover funds than for low-turnover funds due to Corollary 1 ($b_S > b_L$).

Finally, our model also sheds light on the interactions between fund characteristics such as fund size, fees, turnover, and price impact costs. To see this, substituting Eq. (22) into a_h in Eq. (21) yields

$$PI = \sqrt{qfb_h}, \tag{23}$$

which suggests that, although the price impact costs only depend on the fund's alpha opportunity in equilibrium, Eq. (23) 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 Pastor, 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 3 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

[15] 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.

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 (Eq. (21)), the correlation between fund size and price impact costs, or the correlation between fund size and the horizon over which value is added, are ambiguous without controlling for fund turnover.

We now summarize the main conclusions relevant to our empirical analyses:

Empirical Prediction 1. *Fund turnover correlates positively with short-term value added, and negatively with long-term value added.*

Empirical Prediction 2. *Fund turnover correlates positively with the abnormal returns of the fund's short-term holdings before price impact costs.*

Empirical Prediction 3. *Fund turnover correlates positively with price impact costs.*

3 Method of Decomposition

To measure the value added at different investment horizons, 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.[16] The value added from all trades (purchases and sales) in the past 1 to 240 days can be calculated using the same framework.[17].

The common practice of analyzing investors' trading performance in the transaction 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 (from days to quarters depending on the study). Since our study focuses on a fund's value added over different investment horizons and the specific trade-offs it faces when choosing between short-term and long-term investment opportunities, we need to allow for different horizons for different holdings/trades of the same fund. Therefore, we deviate from this common practice and decompose the daily value added of mutual funds based on the past length of their holding periods. The main advantages of this decomposition are that (1) it keeps track of funds' actual holdings after their trades, and (2) it accounts for both short-term and long-term trading performance in a unified framework. The first is important because funds may have already sold those stocks before a fixed time period, and the second one is important because

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

[17] A decomposition of the fund's value added based on all the trades (i.e. both purchases and sales), is shown in Section A.2

funds may sacrifice their short-term trading profits for a better long-term performance as illustrated in our model.

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:

$$VA_t = \sum_i H_{i,t-1} R_{i,t} + \sum_i V_{i,t} R^e_{i,t}. \tag{24}$$

$H_{i,t-1}$ is the fund's holding of stock i at the end of day $t-1$ in dollars. For $R_{i,t}$ we use the abnormal returns based on the Capital Asset Pricing Model (CAPM) in the benchmark analysis and use Fama–French three-factor model and Fama–French–Carhart four-factor model in robustness analyses.[18] $V_{i,t}$ is the fund's trading amount of stock i in day t, which is positive for purchases and negative for sales, and $R^e_{i,t}$ is defined as

$$R^e_{i,t} = (P^c_{i,t} - P^e_{i,t})/P^e_{i,t}, \tag{25}$$

where $P^e_{i,t}$ is the execution price and $P^c_{i,t}$ is the closing price for stock i on day t. Just as for $R_{i,t}$, we adjust $R^e_{i,t}$ based on the CAPM (as well as the Fama–French three-factor model, and Fama–French–Carhart four-factor model). Since the exact time of trade execution within a day is not reported in the Abel Noser dataset, we assume trades on average occur at mid-day when adjusting $R^e_{i,t}$. Given that the daily risk premiums are negligible, this does not materially affect our results. For example, the contribution of trades to fund value added through market exposure within the same day is approximately USD 9000 per year, which is only 0.1 bps of the average funds' TNAs and 2 bps of average value added of funds in our sample.

In summary, the first term on the right-hand side of Eq. (24) 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 the net purchases in the past n days by

$$B^{s(n)}_{i,t-1} = \begin{cases} 0\ , & \text{if } H^{s(n)}_{i,t-1} \leq 0 \\ H^{s(n)}_{i,t-1}, & \text{if } H^{s(n)}_{i,t-1} > 0 \end{cases}. \tag{26}$$

[18]The alphas of stocks are calculated using one-year rolling regressions. One reason to use the CAPM as the benchmark model is that fund investors care about CAPM alphas, not multifactor alphas, as is documented in Berk and van Binsbergen (2016) and Blocher and Molyboga (2017).

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

$$B_{i,t} = \begin{cases} 0 \ , & \text{if } V_{i,t} \leq 0 \\ V_{i,t}, & \text{if } V_{i,t} > 0 \end{cases} . \tag{27}$$

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

$$H^{s(n)}_{i,t-1} = B^{s(n)}_{i,t-1} + S^{s(n)}_{i,t-1}, \tag{28}$$

and

$$V_{i,t} = B_{i,t} + S_{i,t}. \tag{29}$$

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 in the past n days), $B^{s(n)}_{i,t-1}$, and the holding that has been in the portfolio longer than n days, $H^{l(n)}_{i,t-1}$:

$$H_{i,t-1} = B^{s(n)}_{i,t-1} + H^{l(n)}_{i,t-1}. \tag{30}$$

[19] [20] Substituting Eq. (29) and (30) into Eq. (24) gives us

$$VA_t = \left(\sum_i B_{i,t} R^e_{i,t} + \sum_i B^{s(n)}_{i,t-1} R_{i,t} \right) + \sum_i H^{l(n)}_{i,t-1} R_{i,t} + \sum_i S_{i,t} R^e_{i,t}, \tag{31}$$

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 the parenthesis) and value added from holdings longer than n days (the third term).[21] The last term adjusts for stocks sold on day t.[22]

Alternatively, we can decompose the fund value added based on all the trades, including both purchases and sales, as described in Section A.2. Our main finding that funds specialize and add

[19] Refer to Table 8 for the fraction of holdings by past length of holding periods and by fund categories.

[20] 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 still in this fund's portfolio at the end of day $t-1$. This measure of holding longer than n day takes the shares sold and bought back shortly after into account. Our result stays almost the same if we measure it using shares that were always in the portfolio in the past n days.

[21] One may argue that if funds hold on to 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 (Eq. 24 & 31). 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.

[22] The effect of intra-day sales on the value added of a fund is, on average, USD 0.08 million per year, which is only 0.7 bps of the average fund TNA. We include it for the completeness and accuracy of the calculation of value added.

value at different investment horizons does not change.[23]

4 Mutual Fund Data and Measures of Trading Costs

4.1 Sample of Mutual Funds

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

Abel Noser Solutions (formerly ANcerno Ltd. and Abel/Noser Corporation) 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 dataset that we obtained contains detailed information regarding trading amounts, trading times, and trading costs. One drawback is that the dataset does not disclose the actual identities of the funds.[24] We identify the mutual funds in this dataset by matching the changes in the stock holdings indicated by the transaction data in Abel Noser with the changes in the holdings reported in Thomson Reuters. Following Busse, Chordia, Jiang, and Tang (2020), for each fund in Abel Noser (as identified by "clientmgrcode") and for each quarter, we compute the change in holdings (i.e., across all trades with shares adjusted for splits and distributions) for that fund in each stock during that quarter. For each fund in Thomson Reuters, we also compute split-adjusted changes in its holdings every quarter.[25] We then compare the change in quarterly holdings stock by stock for funds in Abel Noser and Thomson Reuters to find a match. We further match these Thomson Reuters funds to the CRSP mutual fund data through the MFLINKS data provided by WRDS (see Wermers [2000]). We keep active equity funds for this analysis by dropping all funds with less than an average of 70% of their holdings in equities or an indicator for index funds, as reported in the CRSP mutual fund database. We then exclude funds with a turnover of less than 70% of the turnover reported in the CRSP mutual fund database to ensure that it is not only a fraction of the trades being reported to Abel Noser. Lastly, we manually verify the matches identified one by one using fund names from Thomson Reuters and the CRSP mutual fund database, and a client manager name list (with the names for all "clientmgrcode") disclosed by Abel Noser in 2011.[26] We end up with 332 active equity funds that are properly matched for our

[23]The results of decomposition based on all the trades are available upon requests.

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

[25]Most funds in Thomson Reuters report their holdings at the end of each quarter. For those periods that funds report semiannually or not at the end of each quarter, we calculate the changes of holdings between two adjacent report dates in both Thomson Reuters and Abel Noser for comparison.

[26]The name list provided by Abel Noser only includes vague abbreviations for fund managers in the same fund family. Therefore, we cross-check those abbreviations with fund names provided in the CRSP mutual fund database

analysis (refer to Section A.1.2 for the details of matching quality).[27]

Table 1 reports the summary statistics of these 332 mutual funds and, for comparison, the summary statistics of all equity mutual funds in the CRSP mutual fund database. The characteristics of the 332 funds are similar to the characteristics of an average fund in the CRSP mutual fund database, both, in the aggregate as well as separately for each year. In addition, the average value-weighted fund net return of these 332 mutual funds is 5.15% per year, close to the 4.94% per year for all equity mutual funds in the CRSP mutual fund database. The only difference is that they are, on average, slightly larger than the average fund in CRSP. Abel Noser's clients are more likely to be large funds than small funds. This difference is also documented by other studies using Abel Noser data, such as Puckett and Yan (2011), who also provide evidence that institutions are not submitting their trades to Abel Noser selectively.[28]

[Insert Table 1 about here]

We construct the daily holdings of the 332 mutual funds by merging the transaction data in Abel Noser 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.[29]

4.2 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 intra-day implicit costs related to the price impact of trades, and the multi-day implicit costs related to the liquidity consumption/provision across days.

Trades' commissions, taxes, and fees are reported directly by Abel Noser Solutions in dollars. We calculate their (negative) contribution to daily fund value added as the average dollar amount

and Thomson Reuters, and only keep those matches that are certainly correct. It is important to note that our holdings and name-matching procedures are performed at the fund level as identified by "clientmgrcode" in the Abel Noser data, rather than at the institution/fund family level as identified by "managercode." Please refer to the Appendix for more details about the matching procedure and the selection of funds for our analysis. See the Appendix in Puckett and Yan (2011) for more details about the different identifiers in the Abel Noser data.

[27] The percentage of Thomson Reuters quarterly holdings matched with Abel Noser transaction data for our sample of mutual funds is higher than that reported in the Appendix of Puckett and Yan (2011) for 68 institutions that they obtained a complete name list from Abel Noser.

[28] See the Appendix of Puckett and Yan (2011).

[29] Please refer to the Appendix for more details of the construction of daily holdings.

of those costs per day. We measure the intra-day price 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. The expression is

$$ES_{i,t} = D_{i,t} \frac{P^e_{i,t} - P^0_{i,t}}{P^0_{i,t}}, \tag{32}$$

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 costs of this trade 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. Funds split large trades into smaller trades to reduce price impact. The intra-day price impact costs measured by the execution shortfalls are paid during trade executions. The total contribution of intra-day price impact costs to a fund's daily value added for all trades on day t is

$$ES_t = \sum_{i=1}^{I} (D_{i,t} V_{i,t} ES_{i,t}), \tag{33}$$

with the intra-day 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, $ES_{i,t}$.

Although the execution shortfall captures a trade's liquidity consumption/provision within a day, it does not capture a trade's liquidity consumption/provision across days. A stock's expected return in the coming days may be positive or negative if the current stock price is either suppressed or elevated by a liquidity shock. A trader may trade with or against multi-day liquidity signals. We measure the multi-day liquidity costs using the abnormal returns of stocks implied from the short-term reversal strategy. Intuitively, a fund trading in accordance with a short-term reversal strategy benefits from providing liquidity to the market, whereas a fund trading against the short-term reversal strategy pays the costs for consuming liquidity. We construct the short-term reversal signal based on the past week's market-adjusted returns. Following de Groot, Huij, and Zhou (2012), we skip one day before constructing the portfolio to control for the price impact of trades. Thus, the short-term reversal signal on day t is based on the returns from $t-6$ to $t-1$. We sort all stocks in our sample period into quintiles based on their short-term reversal signals on each day t and use the average CAPM alpha of all stocks in the same quintile as the expected return for all stocks in that quintile. The multi-day liquidity costs of each fund on day t caused by trades within the past

n days is measured as

$$SR_t^{s(n)} = \sum_{i=1}^{I} H_{i,t-1}^{s(n)} R_{i,t}^{sr}, \tag{34}$$

where $R_{i,t}^{sr}$ is the expected return of stock i on day t according to the short-term reversal quintile that stock i belongs to. Therefore $SR_t^{s(n)}$ captures the contribution of the multi-day liquidity consumption/provision of the fund's trades in the past n days $H_{i,t-1}^{s(n)}$ to its value added on day t. We use $SR_t^{s(n)}$ of the trades in the past 10 days as a measure of the multi-day liquidity cost.[30] Notably, the abnormal return of the short-term reversal strategy is an incomplete measure of multi-period liquidity costs because liquidity shocks can potentially last longer (e.g., Coval and Stafford [2007]).

5 Decomposing Fund Value Added by Investment Horizons

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 based on their horizon-specific skills (value added), which takes heterogeneous price impacts costs of investing at different investment horizons into account.

5.1 Low-Turnover Funds vs. 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 Eq. 14), as well as funds that 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 separately both the value added of high-turnover and low-turnover funds. 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

[30] Trades more than 10 days ago have nearly no effect on this measure of multi-day liquidity costs.

holdings of high-turnover funds add more value than the short-term holdings of low-turnover funds, and vice versa. (*Empirical Prediction 1*). Third, we investigate whether 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 (*Empirical Prediction 2*). Fourth, we study the sources of their profits at different investment horizons.

5.1.1 The Dispersion and Persistence of Fund Turnover

We sort funds into quintiles based on their average turnover every quarter. Table 2 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 of 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 785% (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 three to four (=785%/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.

[Insert Table 2 about here]

[Insert Figure 1 about here]

5.1.2 Value Added of Holdings by Investment Horizons

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 Eq. (14)) and whether the value added of low-turnover funds' long-term holdings are significantly positive ($\hat{J}_L^* > 0$). Figure 2 plots the value added of holdings shorter than 240 days (net purchases within 240 days) calculated using Eq. (31) and their 90% confidence intervals. The top panel is for low-turnover funds (quintile 1) and the bottom panel is for high-turnover funds (quintile 5). The left vertical axis is the value added measured in millions

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

of dollars and the right vertical axis is the corresponding contribution of holdings to fund's annual CAPM gross alpha, which is the value added divided by the TNAs of the fund. As shown in the bottom panel, high-turnover funds' holdings shorter than 10/20/40 days add USD 3.3/4.2/6.6 million value per year (0.81%/1.02%/1.61% in terms of annual gross alpha), which is statistically significant at the 10% significance level, and their holdings shorter than 240 days add as much as USD 10.7 million value per year (2.59% in terms of annual gross alpha). In contrast, the top panel shows that low-turnover funds' holdings shorter than 10/20/40 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). Table 3 reports the results and significance levels for the value added from holdings shorter than 240 days, the value added from holdings longer than 240 days, as well as the total value added from all holdings. The second last row of column (1) in Table 3 Panel A reports that low-turnover funds' holdings longer than 240 days add a significant USD 62.9 million of value per year (2.72% 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. Whereas high-turnover funds' holdings longer than 240 days destroy USD 4.1 millions of value (-1.00% 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 do not supports the first part of *Empirical 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 do not confirms the second part of *Empirical 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.

[Insert Figure 2 about here]

[Insert Table 3 about here]

To further explore the sources of funds value added at different investment horizons, we redo the above analysis now using the Fama–French three-factor abnormal returns (FF3), and the Fama–French–Carhart four-factor abnormal returns (FFC4). The results are reported in Table 3. By comparing the low-turnover funds' value added based on CAPM, in column (1), and 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 exposures to the size factor or value factor. Since the average holdings of low-turnover funds tilt toward value stocks and large-cap stocks (as report in Panel D of Table 2), their value added from long-term holdings are mainly from exposures 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 size and value strategies (or strategies highly correlated with these two) to harvest long-term alphas. In addition, we plot in Figure 3 high-turnover funds' value added from net purchases within 240 days based on all three models, column (4) to (6) of Table 3. It shows 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 almost disappear 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 largely use momentum (or strategies highly correlated with momentum) to harvest short-term alphas.[32] Consistently, as reported in Panel D of Table 2, the average holdings of high-turnover funds tilt towards momentum stocks. Finally, as reported in Panel A of Table 2, the average value added of all funds and funds in turnover quintile 2 and 3 remain positive and significant after controlling for size, value and momentum factors, indicating that mutual funds, especially those with medium or slightly lower turnover rates, do profit from strategies other than size, value, and momentum.

[Insert Figure 3 about here]

5.1.3 Alpha Opportunities before Price Impact Costs

Next, we investigate *Empirical Prediction 2* 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 amounts, rather than in dollar amount (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 (1) the alpha opportunities captured by high-turnover funds shortly after their trades are substantially larger than that captured by low-turnover funds; and (2) while the alpha opportunities of high-turnover

[32]Since the momentum factor does not take into account the price impact costs of trades whereas our value added measure does, the value added attributable to the momentum strategy may be smaller.

funds diminish in the following year, that of low-turnover funds increase gradually. These results indicate that high-turnover funds and low-turnover funds are profiting from different sources of alpha opportunities, which is consistent with our finding in the previous section that the short-term value added of high-turnover funds are mainly from their exposures to the momentum factor, whereas the long-term value added of low-turnover funds are mainly from their exposures to the value factor.

[Insert Figure 4 about here]

[Insert Table 4 about here]

Figure 4 plots the alpha opportunities captured by the net purchases before price impact costs in the past 10 to 240 days and their 90% confidence intervals for low-turnover funds and high-turnover funds separately. We compute these alphas by dividing the value added of net purchases in Eq. (31) plus the price impact costs of purchases (measured by the execution shortfall in dollar as in Eq. 32 and 33) by the total dollar amount of net purchases. The results are reported in Table 4. As shown in the bottom panel of Figure 4, stocks purchased by high-turnover funds in the past 10 days have annual alphas of 16.31% before price impact costs which is statistically significant. It diminishes to 7.16% once this period is extended to 40 days, and to an insignificant 3.86% once extended to 240 days. In contrast, stock purchases by low-turnover funds in the past 20 to 50 days have negative or zero alpha, and it becomes positive for 60 days to 240 days (with an annual alpha of 4.66%) and is not statistically different from zero.

To summarize, we find that high-turnover funds and low-turnover funds are profiting from different alpha opportunities, instead of the same opportunity with different trading frequencies. We document that they are (1) not from the same source, (2) do not have the same magnitude, and (3) realize at different times after trades.

5.1.4 Tests of Differences between Low-Turnover Funds and High-Turnover Funds by Investment Horizon

Table 5 tests *Empirical Prediction 1* & *2* formally in the cross section of mutual funds. The second column of Panel A reports the difference between the value added of high-turnover funds and low-turnover funds for each holding period, which is averaged across days and annualized. According to their corresponding p-values reported in the third column of Panel A, the null hypothesis of the first part of *Empirical Prediction 1* that *low-turnover funds have a higher value added than high-turnover funds from holdings shorter than 40 days* is rejected at the 95% confidence level. Further, the null hypothesis of the second part of *Empirical Prediction 1* that *high-turnover funds have a higher value* *added from holdings longer than 240 days than low-turnover funds* is rejected at the 90% confidence level. The difference in their value added becomes smaller and insignificant when the holding period increases to 120 and 240 days.

[Insert Table 5 about here]

However, the value added distribution 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-statisticis t-distributed. Therefore, we also use an alternative measure of statistical significance based on the order statistics developed in Berk and van Binsbergen (2015), which 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 *Empirical Prediction 1*. Under this measure (as reported in the fourth and fifth columns of Panel A), the null hypothesis of the first part of *Empirical Prediction 1* is reject at the 95% confidence level for holdings shorter than 60 days, and the null of the second part is rejected as well at the 95% confidence level for holdings longer than 240 days.

Panel B of Table 5 tests *Empirical Prediction 2*. Under both the original measure based on α_h and the new measure based on order statistics, the null hypothesis that low-turnover funds have a higher short-term alpha before price impact costs than high-turnover funds is rejected at the 95% confidence level for holdings shorter than 240 days in all 12 cases, and it is rejected at the 99% confidence level in seven out of eight cases for holdings shorter than 60 days.

5.2 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 as much as funds investing in long-term opportunities do, price impact costs are higher for short-term opportunity than long-term opportunity per dollar of investment (*Corollary 1*). In equilibrium, funds choosing short-term opportunity have a higher portfolio alpha before price impact costs, which covers the higher price impact costs of investing in the short-term than in the long-term (*Proposition 3*). Therefore, there is a positive correlation between fund turnover and the realized price impact costs (*Empirical Prediction 3*).

Table 6 reports the price impact costs measured by execution shortfall (as defined in Eq. 32) and the multi-day liquidity costs based on the exposure of trades to short-term reversal effects (as defined in Eq. 34)—Both are as a percentage of dollar trading amounts. Panel C of Table 6 reports the price impact costs by fund turnover quintiles. Consistent with *Empirical Prediction 3*, the execution shortfall increases monotonically from -0.08% for low-turnover funds (quintile 1) to 0.48% for high-turnover funds (quintile 5), and the difference of 0.57% is both economically and statistically significant. Moreover, the negative execution shortfall of low-turnover funds suggests that they are actually profiting from providing liquidity to other investors during the execution of their trades. Consistently, the multi-day liquidity costs of high-turnover funds are significantly higher than that of low-turnover funds, and the negative multi-day liquidity costs of low-turnover funds suggest that they are providing liquidity across days as well.

[Insert Table 6 about here]

Moreover, if we hold the fee constant in Eq. (23) of our model, it predicts that (1) controlling for fund size, there is a positive correlation between fund turnover and price impact costs because of *Corollary 1* ($b_S > b_L$), and (2) the price impact costs increase more with fund size for high-turnover funds than for low-turnover funds, also because of *Corollary 1*. To test these predictions, we also sort funds into size quintiles based on their TNAs at the end of each month.[33] We then construct 25 portfolios based on the intersections of these fund turnover and size quintiles. Consistent with the prediction (1) above, the execution shortfall of high-turnover funds (turnover quintile 5) is 0.19% to 0.79% higher than low-turnover funds (turnover quintiles 1) controlling for fund size (as reported in Panel A of Table 6). These number are both economically and statistically significant for all fund size quintiles. This result is consistent with the ticket-level analysis in Busse, Chordia, Jiang, and Tang (2020), which shows that fund turnover stays a significant determinant after controlling for both fund-level and ticket-level characteristics, such as fund size, investment styles, ticket size, stock liquidity, and volatility. Panel A of Table 6 also shows that, while the execution shortfall increases monotonically and significantly with fund size for high-turnover funds (turnover quintile 5), it is insignificant or negative for the other four turnover quintiles. This result confirms the prediction (2) above that the price impact costs increase more with fund size for high-turnover funds than for low-turnover funds. Similarly, the multi-day liquidity costs of high-turnover funds is statistically higher than low-turnover funds for four out of five size quintiles (as reported in Panel B of Table 6), whereas the multi-day liquidity costs of large funds is only statistically higher than small funds for high-turnover funds in turnover quintile 5.

[33] More accurately, Eq. (23) of our model suggests that we should sort by the product of fund size and fee. Here, we follow the convention of mutual fund literature of sorting funds by fund size to make the results directly comparable with studies such as Busse, Chordia, Jiang, and Tang (2020). Since the variation of fee is substantially smaller than the variation of 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 fee.

Lastly, Panel D of Table 6 shows that the price impact costs measured by execution shortfall and multi-day liquidity costs are both non-monotone in fund size without controlling for fund turnover, which is consistent with the prediction in Proposition 3 that, in equilibrium, the magnitude of price impact costs only depends 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 the fund turnover and price impact costs b_h into account. This non-monotone relation between fund size and price impact costs is consistent with the empirical evidence of Busse, Chordia, Jiang, and Tang (2020), who find 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 non-monotone relation.

5.3 Large Funds vs. Small Funds

Our model (Eq. 21) shows that the equilibrium fund size is a function of the fund's skill (value added) and fee only. The skill (value added), in turn, is dependent on the price impact costs (scalability of the strategy). That is, for funds with the same compounding alpha a_h, the equilibrium fund size is larger for low-turnover funds, which specialize in long-term investing, than high-turnover funds, which specialize in short-term investing, because of the larger price impact costs of investing in the short-term ($b_S > b_L$ as in *Corollary 1*).

To investigate this prediction empirically, we sort funds into size quintiles as in last section. Table 7 reports the average value added of funds, fund characteristics, trading costs, and stock characteristics of holdings for each fund size quintile. Consistent with our prediction, Table 7 shows that (1) the average turnover (total trading amounts of purchases and sales divided by the fund TNA) of large funds is only 205% per year, which is substantially lower than the 372% per year turnover for small funds (as reported in Panel B). This means that large funds on average change their portfolios about once (205%/2) per year, whereas small funds change their portfolios about twice (372%/2) per year. (2) About 84% of large funds' value added are from their holdings that have been in their portfolio for longer than 240 days (as reported in Panel A). (3) Large funds hold more value stocks, large-cap stocks, and less momentum stocks than small funds do (as shown in Panel D), indicating that large funds adopt strategies at longer-term. Note that the difference of fund turnover between large funds and small funds (205% vs. 372%) is substantially smaller than that difference between low-turnover funds and high-turnover funds (29% vs. 785%), as reported in Table 2 and Figure 1. This result supports our *Proposition 1* that funds choose their turnovers (investment horizons) based on their horizon-specific skills, not fund size. Moreover, Panel A of Table 7 shows that, for all fund size quintiles, the value added from holdings longer than 240 days are consistently and significantly positive and explain the majority of their value added, further confirming that the correlation between fund size and the horizon over which the value is added is ambiguous when horizon-specific skills are omitted.

[Insert Table 7 about here]

Next we compare the value added of large funds and small funds' holdings and trades by investment horizon. Figure 5 shows that small funds' holdings shorter than 30 days add a statistically significant USD 0.34 million of value (76 bps in terms of annual gross alpha), and it reverses to zero within half a year, whereas large funds' holdings add USD 35.5 million of value (46 bps in terms of annual gross alpha) gradually over time in the first 240 days. Our results are consistent with the empirical studies documenting that funds adapt their investment and trading strategies to their fund size and price impact of trades, such as Pollet and Wilson (2008), Busse, Chordia, Jiang, and Tang (2020), and Pastor, Stambaugh, and Taylor (2020). While they focus on the interactions between fund size, stock liquidity, and the diversification of funds' portfolios, we focus on the horizon over which value is added. Moreover, our model points out that, in equilibrium, both fund size and price impact costs are endogenously decided by funds' horizon-specific skills. Holding a fund's skill (value added) constant, fund size is positively correlated with the investment horizon and price impact costs are negatively correlated with the investment horizon. Following the same logic, the correlations between fund size, stock liquidity, and the diversification of funds' portfolios could potentially be an equilibrium outcome of funds' specializations at stock level and market (or industry) level as well.

[Insert Figure 5 about here]

In addition, Panel A of Table 7 shows that the total value added of funds are significantly positive for four out of five fund size quintiles, except for the smallest quintile. Panel B shows that both the average expense ratio and the average turnover decrease as funds become larger. From Panel C we can see that the total trading costs are about the same magnitude of expenses and represent a large fraction of value added, especially for small and mid-sized funds. While commissions are of equal importance to price impact costs (as measured by execution shortfalls) for small funds, price impact costs are more important than commissions for large funds because of their large trade size.

6 Conclusion

In this study, we propose a model where funds specialize at different investment horizons, and they choose their fund turnovers 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 months add a substantial amount of value, whereas holdings of low-turnover funds only add value at longer horizons.

Future research could further investigate on 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 is to explore the sources of the trading skills and signals that generate the value added that we document. Moreover, our analysis focuses on mutual funds that are mostly long-term investors. Conducting a 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.

Figures and Tables

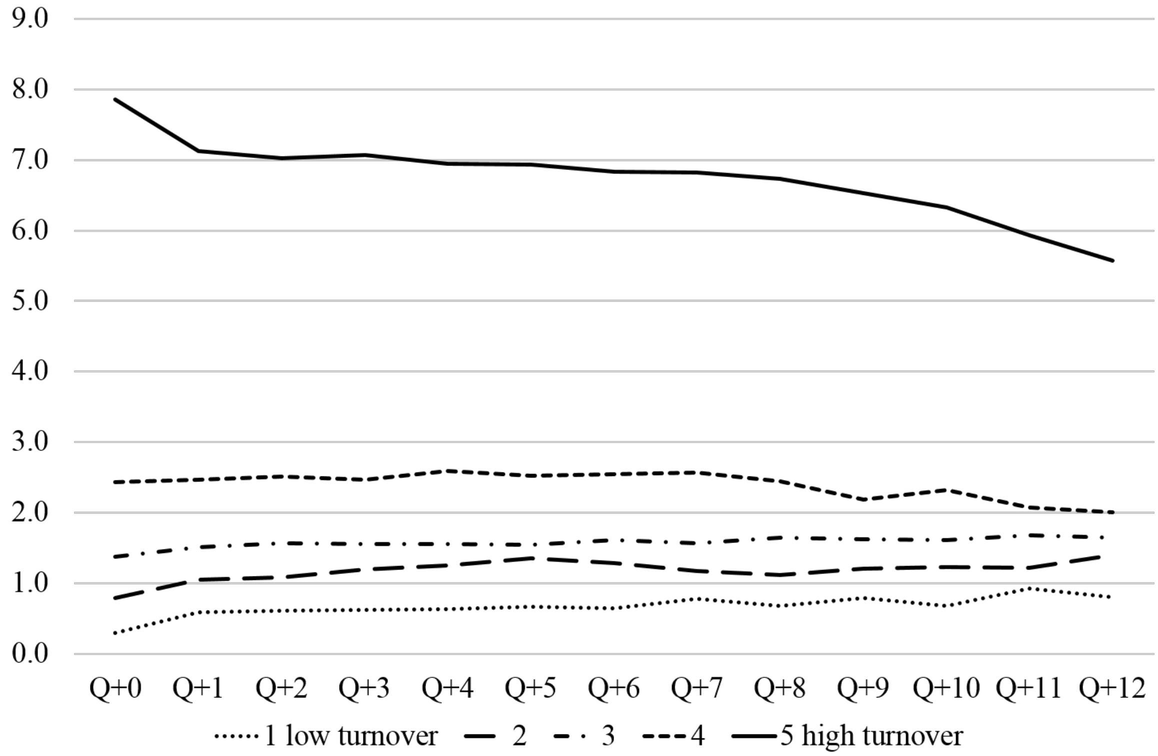


Figure 1: Persistence of Fund Turnover

This figure plots the average turnover of funds for each turnover quintile in the following three years. The turnover plotted here is the 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 is for funds with the highest turnover (quintile 5) and the dotted line at the bottom is for funds with the lowest turnover (quintile 1). The fund turnover is winsorized at 1% level.

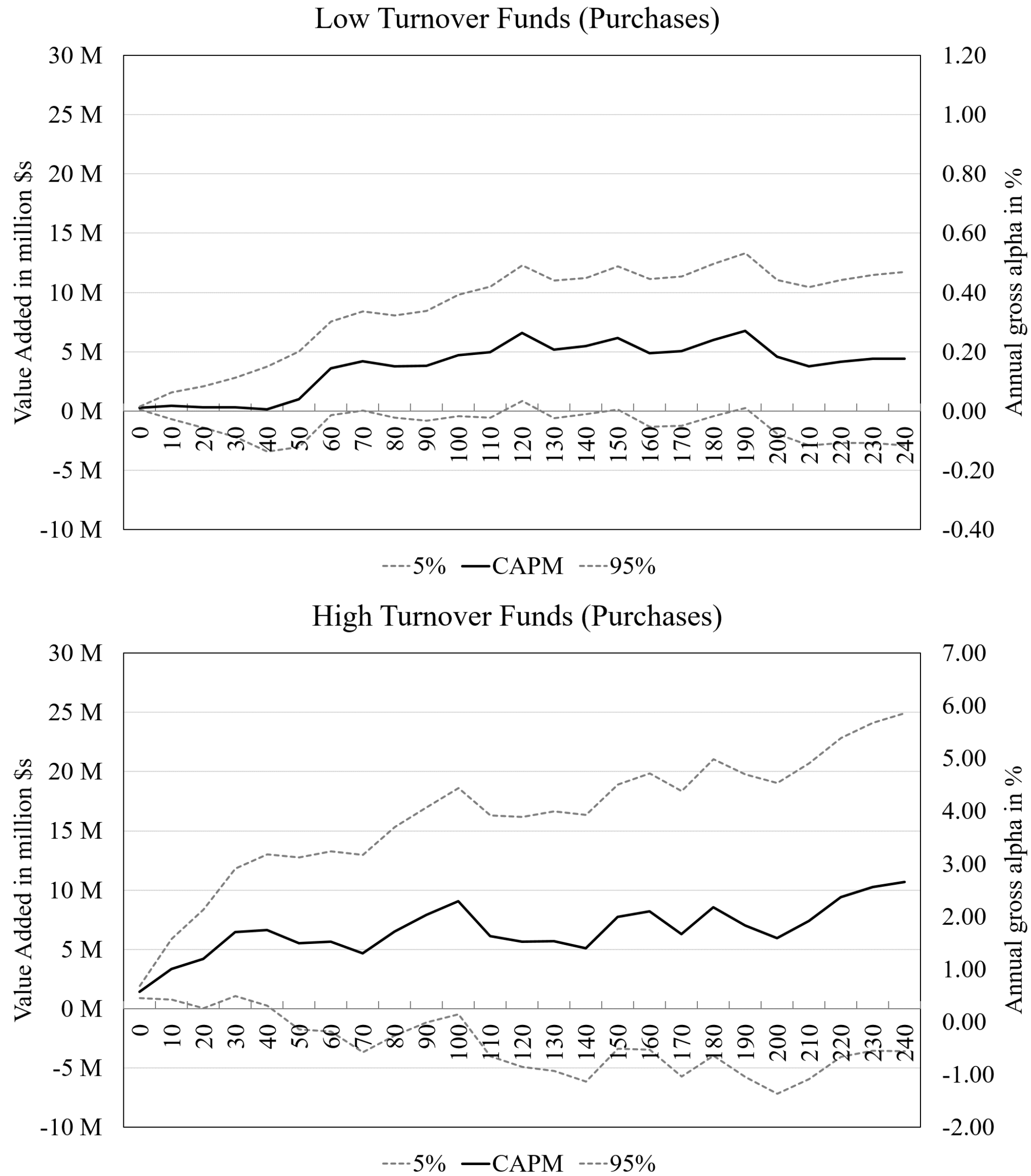


Figure 2: Value Added of Holdings within A Year: Low-Turnover vs. High-Turnover Funds

This figure plots the value added from holdings shorter than 240 days (net purchases in the past 240 days) for low-turnover funds and high-turnover funds separately and their 90% confidence intervals. Funds are sorted into turnover quintiles according to their total turnovers including both purchases and sales every quarter. Quintile 1 is for low-turnover funds and quintile 5 is for high-turnover funds. Value added from purchases in the past n (1 to 240) days is calculated using Eq. (31). The left vertical axis is the value added measured in million dollars. The right vertical axis is the corresponding contribution of net purchases to fund's annual gross alpha, which is the value added divided by the TNAs (total net assets) of the fund. Value Added is equally weighted across fund-day observations and the corresponding contribution to fund's gross alpha is value-weighted by fund TNAs. The CAPM abnormal return of each stock is used for this calculation. Confidence intervals are calculated based on robust standard errors clustered at the day level.

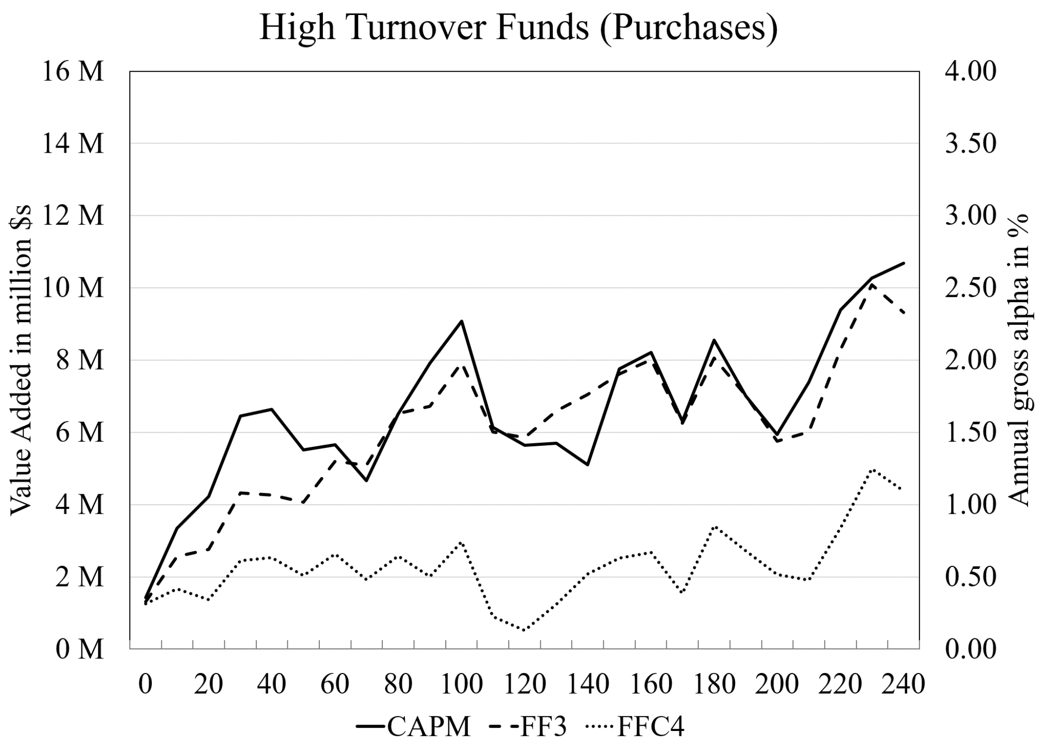


Figure 3: High-Turnover Funds' Value Added of Holdings in One Year

This figure plots the value added from holdings shorter than 240 days (net purchases in the past 240 days) for high-turnover funds using different asset pricing models. The CAPM, Fama–French three-factor model, and Fama–French–Carhart four-factor model are used for this calculation. Funds are sorted into turnover quintiles according to their total turnovers including both purchases and sales every quarter. Quintile 5 is for high-turnover funds. Value added from purchases in the past n (1 to 240) days is calculated using Eq. (31). The left vertical axis is the value added measured in million dollars. The right vertical axis is the corresponding contribution of net purchases to fund's annual gross alpha, which is the value added divided by the TNAs (total net assets) of the fund. Value Added is equally weighted across fund-day observations and the corresponding contribution to fund's gross alpha is value-weighted by fund TNAs. Confidence intervals are calculated based on robust standard errors clustered at the day level.

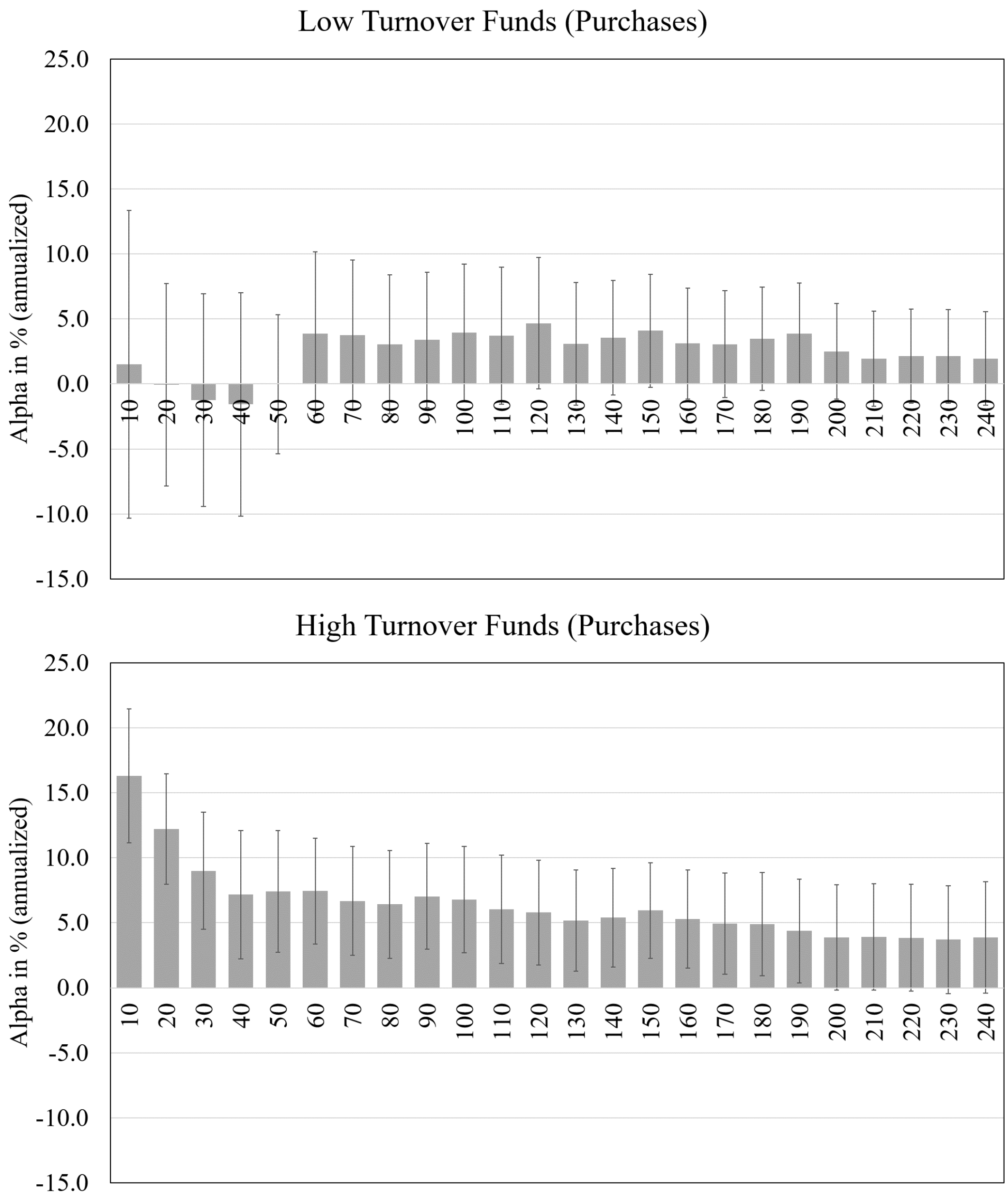
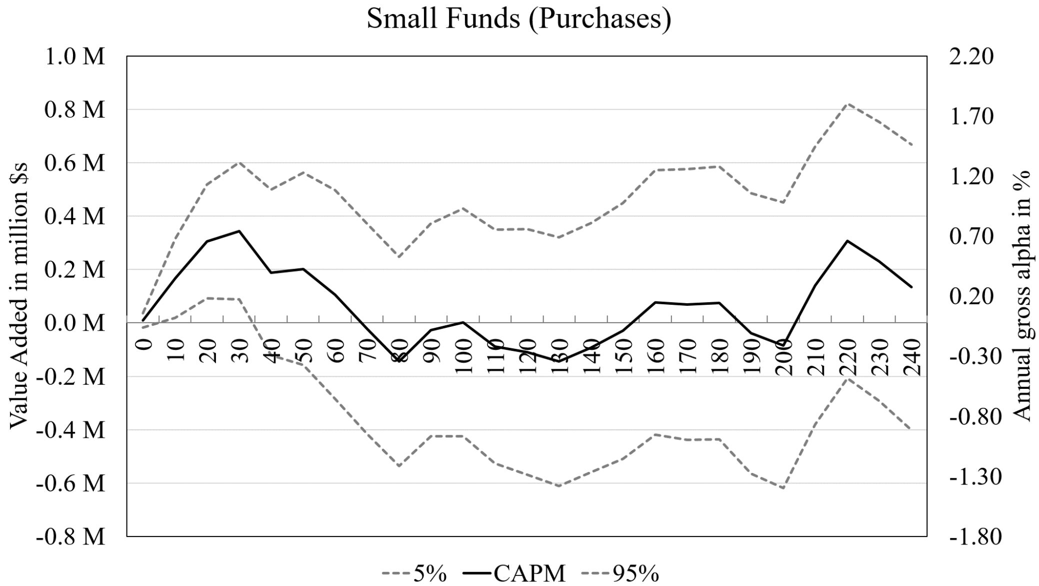


Figure 4: Alpha Opportunities of Net Purchases Before Costs: Low- vs. High-Turnover Funds

This figure plots the alpha opportunities before price impact costs (α_S and α_L in our model) captured by the net purchases in the past 10 to 240 days for low-turnover funds and high-turnover funds separately and their 90% confidence intervals. Funds are sorted into turnover quintiles according to their total turnovers including both purchases and sales every quarter. The alpha opportunities before price impact costs captured by the net purchases in the past n (10 to 240) days is calculated as the value added of net purchases in Eq. (31) plus the price impact costs of purchases in dollar measured by the execution shortfall (as in Eq. 32 and 33), together divided by the total dollar amounts of purchases. The alphas are annualized and value-weighted by the dollar amounts of net purchases. The CAPM abnormal return of each stock is used for this calculation. Confidence intervals are calculated based on robust standard errors clustered at the day level.



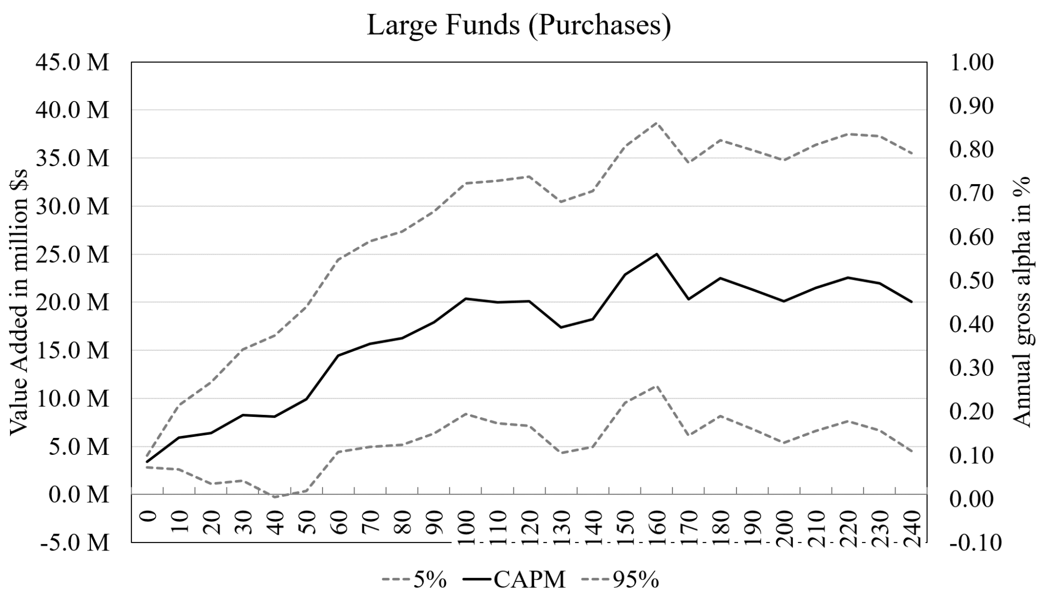


Figure 5: Value Added of Holdings within A Year: Small vs. Large Funds

This figure plots the value added from holdings shorter than 240 days (net purchases in the past 240 days) for small funds and large funds separately and their 90% confidence intervals. Funds are sorted into size quintiles according to their assets under management at the end of each month. Quintile 1 is for small funds and quintile 5 is for large funds. Value added from purchases in the past n (1 to 240) days is calculated using Eq. (31). The left vertical axis is the value added measured in million dollars. The right vertical axis is the corresponding contribution of net purchases to fund's annual gross alpha, which is the value added divided by the TNAs (total net assets) of the fund. Value Added is equally weighted across fund-day observations and the corresponding contribution to fund's gross alpha is value-weighted by fund TNAs. The CAPM abnormal return of each stock is used for this calculation. Confidence intervals are calculated based on robust standard errors clustered at the day level.

Table 1: Summary Statistics

This table reports the summary statistics of the 332 funds used in this study and all equity mutual funds in the CRSP mutual fund database. Panel A is for the sample in this study and Panel B is for the CRSP sample. Column "Year" represents the year of the records. "Num. of Funds" represents the number of funds in the sample. "Fund TNA ($mn)" represents the average fund TNAs in million dollars. "Stock Holding" ("Cash Holding") represents equity (cash) holdings as a percentage of fund TNAs as reported in CRSP, which are available only after 2001. "Turnover (%)" represents the annual turnover reported in CRSP, which is the minimum of the aggregate purchases and the aggregate sales during the calendar year divided by the average TNA of the fund. "Expense Ratio (%)" represents the annual expense ratio and "Management Fee (%)" represents the management fee. "Fund Age" represents the average age of the funds.

Year	Num. of Funds	Fund TNA ($mn)	Stock Holding (%)	Cash Holding (%)	Turnover (%)	Expense Ratio (%)	Manage -ment Fee (%)	Fund Age
Panel A: 332 funds merged								
1999-2010	332	1,288	93.2	4.0	92.8	1.51	0.71	7.8
2001	94	1,190	-	-	120.4	1.60	0.69	6.2
2005	208	1,604	93.4	4.1	87.3	1.54	0.69	7.7
2010	79	844	89.7	3.2	89.6	1.41	0.73	8.4
Panel B: All equity funds in the CRSP mutual fund database								
1999-2010	5,486	1,092	94.1	3.7	97.0	1.39	0.73	7.6
2001	3,427	887	-	-	116.7	1.42	0.75	6.3
2005	3,990	1,125	95.4	3.4	87.9	1.43	0.74	7.8
2010	4,104	1,313	89.9	3.1	87.2	1.26	0.68	9.6

Table 2: Value Added, Fund Characteristics, and Trading Costs by Fund Turnover Quintiles

This table reports the fund value added, fund characteristics, trading costs, and characteristics of holdings for all funds and by funds' turnover quintiles. We sort the 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 separately using Eq. (31). The fraction of value added from holdings beyond 240 days, row "*Fraction*," and the total value added based on Fama–French three-factor model (FF3) and Fama–French–Carhart four-factor model (FFC4) are also reported. Panel B reports fund characteristics. "Expenses" are the product of expense ratios and fund TNAs in million dollars. Panel C separately reports the trading costs for commissions, taxes, and fees, execution shortfalls, and multi-day liquidity costs. Panel D reports the average stock characteristic quintiles 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. The robust standard errors are clustered at the day level. Sig. lvl: *** 0.01, ** 0.05, and * 0.1.

		Turnover Quintiles				
	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	-4.1
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 %)	0.81	1.16	1.42	1.39	1.42	1.45
Expenses (in million $s)	8.80	26.8	14.4	13.5	8.4	6.0
Turnover (buy + sell, in %)	270	29	78	138	243	785
TNA ($million)	1080	2310	1010	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***
- Multi-Day SR Costs	0.1**	-0.5**	-0.5**	0.1	0.2	1.5***
Total	5.2***	-0.2**	1.1***	3.4***	4.3***	19.0***
Panel D: Averge 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

Table 3: Value Added of Holdings: Low-Turnover Funds vs. 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 fund's annual gross alpha for low-turnover funds and high-turnover funds separately. Funds are sorted into turnover quintiles according to their total turnovers 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 Eq. (31). We use CAPM abnormal return (CAPM), Fama–French three-factor abnormal return (FF3), and Fama–French–Carhart four-factor abnormal return (FFC4) of each stock for this calculation separately. 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 which 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 fund's annual gross alpha is the value added divided by the fund TNAs (total net assets). Value added is equally weighted across fund-day observations and the corresponding contribution to fund return is value-weighted by fund TNAs. Robust standard errors are clustered at the day level. Sig. lvl: *** 0.01, ** 0.05, and * 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Low-Turnover Funds (Q1)			High-Turnover Funds (Q5)		
Day	CAPM	FF3	FFC4	CAPM	FF3	FFC4
Panel A: Value added of holdings (in million $s)						
0	0.3***	0.2***	0.3***	1.4***	1.3***	1.3***
10	0.4	0.2	0.3	3.3**	2.6*	1.7
20	0.3	0.3	0.2	4.2*	2.8	1.4
40	0.1	-0.2	0.1	6.6*	4.3	2.5
60	3.6	2.6	2.5	5.7	5.2	2.6
120	6.6	5.4	4.7	5.6	5.9	0.5
240	4.4	2.1	4.5	10.7	9.3	4.4
Holdings > 240 days	62.9*	3.4	19.4	-4.1	-7.9	-5.1
All Holdings	67.5*	5.7	24.1	6.3	1.1	-1.0
Panel B: Contribution to fund's annual gross alpha (in %)						
0	0.01***	0.01***	0.01***	0.35***	0.32***	0.31***
10	0.02	0.01	0.01	0.81**	0.62*	0.40
20	0.01	0.01	0.01	1.02*	0.67	0.33
40	0.01	-0.01	0.00	1.61*	1.03	0.62
60	0.16	0.11	0.11	1.37	1.26	0.64
120	0.28*	0.23	0.21	1.37	1.42	0.13
240	0.19	0.09	0.20	2.59	2.26	1.06
Holdings > 240 days	2.72*	0.15	0.84	-1.00	-1.93	-1.24
All Holdings	2.92*	0.25	1.04	1.54	0.26	-0.24

Table 4: Alphas Opportunities Before Costs: Low-Turnover Funds vs. High-Turnover Funds

This table reports the alpha opportunities before price impact costs (α_S and α_L in our model) captured by funds' net purchases in the past 10 to 240 days for low-turnover funds and high-turnover funds separately. Funds are sorted into turnover quintiles according to their total turnovers including both purchases and sales every quarter. Quintile 1 is for low-turnover funds and quintile 5 is for high-turnover funds. The alpha opportunities captured by the net purchases in the past n (10 to 240) days is calculated as the value added of net purchases in Eq. (31) plus the price impact costs of purchases in dollar measured by the execution shortfall (as in Eq. 32 and 33), together divided by the total dollar amounts of purchases. The alphas are annualized and value-weighted by the trading amounts in dollar. The CAPM abnormal return of each stock is used for this calculation. Robust standard errors are clustered at the day level. Sig. lvl: *** 0.01, ** 0.05, and * 0.1.

	Turnover Quintiles				
Day	1 low	2	3	4	5 high
10	1.51	7.65	14.35***	13.25***	16.31***
20	-0.05	2.42	10.52**	7.04**	12.20***
40	-1.57	2.36	3.88	2.95	7.16**
60	3.86	6.66*	5.54*	1.49	7.45***
120	4.66	6.23**	5.14*	0.40	5.79**
240	1.95	2.19	5.34*	1.52	3.86

Table 5: Differences Between High-Turnover Funds vs. Low-Turnover Funds by Holdings Periods

This table reports the average differences in value added and alpha opportunities (before price impact costs), α_h, between high-turnover funds (quintile 5) and low-turnover funds (quintile 1) by the past length of holding periods, and their associated p-values. Panel A is for value added, and Panel B is for α_h. The differences are annualized and averaged across days. We also report the fraction of days that high-turnover funds have a higher value added or α_h 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 or greater (lesser) for holdings shorter (longer) than 240 days, under the null hypothesis of no differences between high-turnover funds and low-turnover funds.

Panel A: Differences in Value Added

	VA (High − Low)		VA (High > Low)	
Day	Mill \$s	p-value(%)	Freq.(%)	p-value(%)
10	3.0	4.80	52.21	1.00
20	4.8	5.00	52.86	0.15
40	9.7	3.50	52.07	1.45
60	5.5	14.25	52.00	1.75
120	-2.4	65.05	51.03	14.00
240	3.6	29.25	50.95	15.75
Holdings > 240 days	-64.8	7.25	48.43	4.95

Panel B: Differences in Alphas Before Price Impact Costs (α_h)

	α_h (High − Low)		α_h (High > Low)	
	in %	p-value(%)	Freq.(%)	p-value(%)
10	19.44	0.15	53.54	0.00
20	13.13	0.25	52.77	0.15
40	8.90	1.30	52.28	0.80
60	8.81	0.55	52.79	0.15
120	5.80	3.45	52.61	0.30
240	6.95	2.65	51.64	4.20

Table 6: Double Sorting: Price Impact Costs 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 sorted funds into turnover quintiles according to their total turnovers including both purchases and sales every quarter, and we sort funds into size quintiles based on their TNAs at the end of each month. Then, we construct 25 portfolios based on the intersections of these fund turnover and size quintiles. Panel A reports the average execution shortfall, which constitutes 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 Eq. 32). Panel B reports the average multi-day liquidity costs calculated based on the exposure of their trades to weekly short-term reversal effect (as shown in Eq. 34). Panel C reports the price impact costs of trades sorted by fund turnover quintiles only, and Panel D reports the results sorted by fund size quintiles only. All numbers in this table are reported as a percentage of trading amounts in dollars and value weighted across trades. The robust standard errors are clustered at the day level. Sig. lvl: *** 0.01, ** 0.05, and * 0.1.

	Turnover Quintiles					
Fund Size Quintiles	1 low	2	3	4	5 high	(5-1)
Panel A: Execution Shortfall (as % of trading amounts)						
1 small	-0.48***	0.18***	0.19***	0.09***	0.23***	0.70***
2	0.09*	0.15***	0.20***	0.24***	0.28***	0.19**
3	-0.02	0.10	0.14***	0.21***	0.26***	0.27***
4	-0.02	0.09***	0.06	0.16***	0.47***	0.49***
5 large	-0.10***	0.01	0.09***	0.19***	0.69***	0.79***
(5-1)	0.38	-0.17*	-0.10	0.11	0.47***	
Panel B: Multi-Day Liquidity Costs (as % of trading amounts, from short-term reversal)						
1 small	-0.21*	-0.04	-0.07*	-0.01	0.00	0.21*
2	0.00	0.04	-0.02	0.01	0.01	0.01
3	-0.25*	-0.07	0.03	0.04	0.04***	0.28**
4	-0.06	-0.09*	-0.03	0.00	0.05	0.10*
5 large	-0.10***	-0.10**	-0.03	0.03	0.06***	0.16***
(5-1)	0.11	-0.06	0.04	0.04	0.06**	

Panel C: By Turnover Quintiles Only

	Turnover Quintiles					
(as % of trading amount)	1 low	2	3	4	5 high	(5-1)
Execution Shortfall	-0.08*	0.03	0.08**	0.17**	0.48***	0.57***
Multi-Day Liquidity Costs	-0.09**	-0.09**	-0.03	0.02	0.04***	0.14***

Panel D: By Fund Size Quintiles Only

	Fund Size Quintiles					
(as % of trading amount)	1 small	2	3	4	5 large	(5-1)
Execution Shortfall	0.14**	0.27*	0.19**	0.24***	0.12***	-0.02
Multi-Day Liquidity Costs	-0.01*	0.01	0.02**	0.00	-0.01*	0.01

Table 7: Value Added, Fund Characteristics, and Trading Costs by Fund Size Quintiles

This table reports the fund value added, fund characteristics, trading costs, and characteristics of holdings for all funds and by fund size quintiles. We sort funds every month into quintiles based on the funds' TNAs at the end of last month. 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 separately using Eq. (31). The fraction of value added from holdings beyond 240 days, row "*Fraction*," and the total value added based on Fama–French three-factor model (FF3) and Fama–French–Carhart four-factor model (FFC4) are also reported. Panel B reports fund characteristics. "Expenses" are the product of expense ratios and fund TNAs in million dollars. Panel C separately reports the trading costs for commissions, taxes, and fees, execution shortfalls, and multi-day liquidity costs. Panel D reports the average stock characteristic quintiles 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. The robust standard errors are clustered at the day level. Sig. lvl: *** 0.01, ** 0.05, and * 0.1.

		Fund Size Quintiles				
	All Funds	1 Small	2	3	4	5 Large
Panel A: Contribution of Holdings and Trades to Fund Value Added						
Value Added (CAPM)	35.9***	1.8	2.5**	12.2**	27.4***	126.1***
from Holdings < 240 days	4.9**	0.1	0.8**	0.9	1.0	20.0**
from Holdings > 240 days	31.0 ***	1.7*	1.7*	11.4**	26.3***	106.3**
Fraction	*0.86*	*0.94*	*0.66*	*0.94*	*0.96*	*0.84*
Value Added (FF3)	12.0	0.3	1.2	4.7	14.0*	37.0
Value Added (FFC4)	17.1*	-0.5	0.9	5.8	14.8**	59.6
Panel B: Fund Characteristics						
Expense Ratio (in %)	0.81	1.63	1.58	1.41	1.28	0.96
Expenses (in million $s)	8.80	0.7	1.5	3.5	8.0	41.8
Turnover (buy + sell, in %)	270	372	277	274	214	205
TNA ($million)	1080	45	94	250	631	4350
Panel C: Trading Costs						
Explicit Costs						
- Commissions	1.9***	0.2***	0.4***	0.9***	1.9***	6.2***
- Taxes and Fees	0.2***	0.0***	0.1***	0.2***	0.3***	0.3***
Implicit Costs (deducted)						
- Execution Shortfall	3.0***	0.2**	0.7*	1.2**	2.9***	10.1***
- Multi-Day SR Costs	0.1**	0.0*	0.0	0.2**	0.1	0.4*
Total	5.2***	0.5***	1.2***	2.4***	5.3***	17.0***
Panel D: Averge Stock Characteristic Quintile of Holdings						
BM ratio quintiles	3.0	2.9	2.7	2.8	3.1	3.2
Stock-cap quintiles	3.0	2.9	3.0	2.8	2.9	3.3
Momentum quintiles	2.9	3.2	3.2	3.1	2.8	2.6

Table 8: 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 the results for all funds. Panel B reports the 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 Quintiles	1 Small	2	3	4	5 Large
$<$ 20 days	0.10	0.08	0.07	0.06	0.02
$<$ 60 days	0.21	0.17	0.14	0.14	0.06
$<$ 240 days	0.22	0.18	0.18	0.21	0.11
$>$ 240 days	0.78	0.82	0.82	0.79	0.89

A Appendix

A.1 Matching Procedure, Construction of Daily Holding Data, and Matching Quality

A.1.1 Matching and Selection of Mutual Funds and the Construction of Daily Holding Data

Following Busse, Chordia, Jiang, and Tang (2020), if the change in a stock holding for a fund in Abel Noser and a fund in Thomson Reuters matches exactly with each other in a reporting period (usually a quarter), then we call this stock a matched stock between these two funds for that reporting period. We call a period a matched period between a fund in Abel Noser and a fund in Thomson Reuters if the period meets the following three criteria: (i) there are at least five matched stocks, (ii) the number of matched stocks is at least 10% of the number of stocks with changes in holdings as reported in Thomson Reuters for this fund, and (iii) the number of matched stocks is at least 10% of the number of traded stocks by this Abel Noser fund. We consider the funds in Abel Noser and Thomson Reuters a likely match if there is at least one matched period between the two. If there exist likely matches between a given fund in Abel Noser and multiple funds in Thomson Reuters, we choose the best match first by the number of matched periods, then by the ratio of matched stocks in Thomson Reuters, and lastly by the ratio in Able Noser if there is a tie.

Following this procedure, matches between 803 Abel Noser funds and the corresponding Thomson Reuters funds were obtained. There are 564 unique Thomson Reuters funds in this list. Multiple Abel Noser funds may map to the same Thomson Reuters fund for different periods. We further match these Thomson Reuters funds to the CRSP mutual fund database through the MFLINK provided by WRDS. We keep equity funds for this analysis by dropping all funds with less than an average of 70% of their holdings in equity, as reported in the CRSP mutual fund database. We then exclude funds with a turnover calculated based on Abel Noser transaction data less than 70% of the turnover reported in the CRSP mutual fund database to ensure that it is not only a fraction of the trades being reported to Abel Noser. Lastly, we manually verify the previously identified matches using fund names from Thomson Reuters and the CRSP mutual fund database, and a fund name list disclosed by Abel Noser in 2011. 338 equity funds are properly matched. After dropping six index funds, 332 funds remain in our sample for the analysis.

We construct the daily holdings of these 332 mutual funds by merging the transaction data in Abel Noser with the quarterly holdings data in Thomson Reuters. We only include stocks that are ordinary common shares (i.e., share code 10 and 11) in the CRSP stock database and we only keep the fund-quarters with at least one trade in Abel Noser data for our analysis. First, we merge the Abel Noser transaction data with daily stock data in the CRSP at the daily level for all fund-stock-quarters with at least one transaction data reported in Abel Noser database to create a new dataset with fund-stock-day observations. Since the stocks held by funds but were not traded in a given quarter would only show up in Thomson Reuters quarterly holdings data (but not in Abel Noser transaction data), we need to include fund-stock-day observations for those stocks as well. Therefore, for each fund-quarter with at least one trade in Abel Noser data, we merge the daily stock data in the CRSP with holdings data in Thomson Reuters to create a dataset of fund-stock-day observations as well and combine it with the dataset created in the first step.

Next, we add the quarterly holdings information in Thomson Reuters (both prior quarter and current quarter) to this new dataset. Because stocks newly purchased in this quarter have no prior quarter holdings data, and stocks completely sold have no current quarter holdings data, we need to use both the holdings data reported at the end of the prior quarter and the data reported at the end of the current quarter to construct complete daily holdings data in the current quarter. For each fund-stock-day observation in this new dataset, if the prior-quarter holding exists, we generate the daily holding on the basis of the holding at the end of the prior quarter and 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 the transactions in the current quarter to generate the daily holdings.

A.1.2 Matching Quality

In the last section, we detailed how we obtain the 332 matched funds. In this section, we assess the matching quality of these 332 funds, i.e., whether the quarterly holdings change in the Thomson Reuters do agree with the quarterly trading from the Abel Noser database for these funds. The first measure we check is that we compute the percentage of quarterly trades (i.e., quarterly holdings change in the Thomson Reuters or quarterly trading from the Abel Noser database) where Thomson Reuters database and Abel Noser database agree with respect to stock traded and trading direction. For example, assume that a fund buys 8,900 shares of Apple Inc. and sells 4,300 shares of Ford over a particular quarter in Thomson Reuters database. If in the Abel Noser database, this fund buys Apple Inc., and sell Ford in that quarter, then this measure is 100%; and if this fund buys Apple Inc., and buy Ford in that quarter in the Abel Noser database, this measure is 50%. We find that it to be 95.9% of our whole sample. In other words, out of all the quarterly trades, 95.9% of the cases, the Thomson Reuters database agrees with the Abel Noser database in terms of the direction of the trades. On top of this coarse measure, we construct a stringent measure[34] where we require that, for a fund, the quarterly holdings change in the Thomson Reuters database matches the quarterly trading from the Abel Noser database with respect to stock traded, trading direction, and trading quantity (where the number of shares traded matches exactly). We find that out of all the quarterly trades, 64.6% of the cases match exactly in these two databases. This value is significantly higher than the average MATCH3 which is 17% reported in Puckett and Yan (2011). There are a couple of reasons why we find a much higher matching rate: (1) Puckett and Yan (2011) conduct their matching quality assessment at the institution level whereas we conduct it at the fund level. Quote from Puckett and Yan (2011) "institutions are allowed to omit disclosing certain positions for up to one year by seeking confidential treatment through amendments to their original 13F filings. Finally, institutions that are required to submit quarterly 13F filings do not have to disclose positions where the size is less than 10,000 shares and the fair market value is less than $200,000." However, mutual funds need to disclose all their holding positions. So that, we can compare all the holding changes form the Thomson Reuters database with the Abel Noser data. (2) We have a name list provided by Abel Noser so that we can check whether our matched funds have the same name in the Abel Noser database, Thomson Reuters database, and CRSP mutual fund database. (3) We prioritize matching quality when selecting the final sample for our analysis. In addition, we compare the total trading volume of our sample of mutual funds based on the transaction data in the Abel Noser database with the total trading volume implied from the quarterly holding data in Thomson Reuters database to check it completeness of the transaction data. We find that the total trading volume based on the Abel Noser database is 20.2% higher than that implied from the quarterly holding data in Thomson Reuters database, which is consistent with the 20% intraquarter round-trip trades reported in Elton, Gruber, and Blake (2011) for mutual funds and 22.89% reported in Puckett and Yan (2011) for institutional investors. In general, our matching is of high quality our transaction data is relatively complete.

A.2 Decomposition of Value Added based on All Trades

Alternatively, we can decompose the fund value added based on all the trades, including both purchases and sales, as follows.[35] Our main finding that funds specialize and add value at different investment horizons stays.

We decompose a fund's holding at the end of day $t-1$, $H_{i,t-1}$, into the change in holding caused by trades within the past n days (10 to 240 days), $H^{s(n)}_{i,t-1}$, and the holding $n+1$ days ago, $H^{p(n)}_{i,t-1}$.

[34] This measure is defined in the same way as MATCH3 in the Internet appendix of Puckett and Yan (2011).

[35] The results of decomposition based on all the trade are available upon requests.

The expression of this decomposition is

$$H_{i,t-1} = H^{s(n)}_{i,t-1} + H^{p(n)}_{i,t-1}, \tag{35}$$

where $H^{s(n)}_{i,t-1}$ can be of either sign while $H^{p(n)}_{i,t-1}$ is non-negative.

Using this holdings decomposition, we decompose the fund's value added on day t into the value added from trades on the same day, value added from the changes in holdings in the past n days (10 to 240 days), and value added from the holdings n days ago:

$$VA_t = \left(\sum_i V_{i,t} R^e_{i,t} + \sum_i H^{s(n)}_{i,t-1} R_{i,t}\right) + \sum_i H^{p(n)}_{i,t-1} R_{i,t}. \tag{36}$$

The first and second terms on the right-hand side of Eq. (36) together (in the parenthesis) measure the contribution of all trades (purchases and sales) within n days to the fund's daily value added after price impact costs, and the last term measures the value added from the holdings n days ago.

A.3 Model Proofs

Proof of Lemma 1:

Proof. Because the last term $\beta^{T_h-1}\left(\mathrm{E}[R_h]q_h + \beta J\right)$ in Eq. (2) is unaffected by the choice of the fund, we can convert the maximization problem into the following minimization problem:

$$\min_{(w_1, w_2, \ldots, w_{T_h}) \in \mathcal{W}} \sum_{\tau=1}^{T_h} \beta^{\tau-1} C(w_\tau). \tag{37}$$

Because the non-negativity constraint never binds, the Lagrangian of the problem is given by

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

Then, the first order condition is given by

$$w_\tau = \beta^{-(\tau-1)} \frac{\lambda}{a} \text{ for all } \tau = 1, 2, .., T_h, \tag{38}$$

and

$$\sum_{\tau=1}^{T_h} w_\tau = q_h. \tag{39}$$

Summing Eq. (38)'s overall τ's yields

$$\sum_{\tau=1}^{T_h} w_\tau = \frac{\lambda}{a}\Gamma_h. \tag{40}$$

By substituting Eq. (39) into Eq. (40) and solving for λ, we have

$$\lambda = \frac{aq_h}{\Gamma_h}. \tag{41}$$

Substituting Eq. (41) into Eq. (38) gives Eq. (5), from which Eq. (6) is immediate. $\square$

Proof of Proposition 1:

Proof. Let us first define the present value of trading profits for investment opportunity h as Π_h:

$$\Pi_h \equiv -\frac{bq_h^2}{2\Gamma_h} + \beta^{T_h-1}\alpha_h q_h. \tag{42}$$

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

$$J_S = \Pi_S + \beta^{T_S} J = \Pi_S + \beta^{T_S} J_S, \tag{43}$$

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

$$\hat{J}_S = J_S > J_L = \Pi_L + \beta^{T_L} J \geq \Pi_L + \beta^{T_L} J_L \geq \hat{J}_L. \tag{44}$$

Now, we prove the if part. Suppose that $\hat{J}_S > \hat{J}_L$. Then,

$$J \geq \hat{J}_S > \frac{\Pi_L}{1-\beta^{T_L}}, \tag{45}$$

which implies

$$J > \Pi_L + \beta^{T_L} J = J_L. \tag{46}$$

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

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

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