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Do Funds Make More When They Trade More?

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Abstract

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Do Funds Make More When They Trade More?

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ABSTRACT

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Mutual funds invest trillions of dollars on behalf of retail investors. The lion's share of this money is actively managed, despite the growing popularity of passive investing.[1] Whether skill guides the trades of actively managed funds has long been an important question, given active funds' higher fees and trading costs. We take a fresh look at skill by analyzing time variation in active funds' trading activity. We explore a simple idea: A fund trades more when it perceives greater profit opportunities. If the fund has the ability to identify and exploit those opportunities, then it should earn greater profit after trading more heavily.

We formalize this idea by developing a model of fund trading in the presence of time-varying profit opportunities. Each period, funds identify opportunities to establish positions that yield profits in the subsequent period, net of trading costs. A fund's optimal amount of turnover maximizes its expected profit, conditional on equilibrium prices. Profit opportunities vary over time, jointly determining turnover and performance. A fund trades more in periods when it has more profit opportunities. Our model's key implication is a positive time-series relation between fund turnover and subsequent fund performance.

Consistent with the model, we find that a fund's turnover positively predicts the fund's subsequent benchmark-adjusted return. This new evidence of skill comes from our sample of 3,126 active U.S. equity mutual funds from 1979 through 2011. The result is significant not only statistically but also economically: a one-standard-deviation increase in turnover is associated with a 0.66% per year increase in performance for the typical fund. Funds seem to know when it's a good time to trade.

We focus on the time-series relation between turnover and performance for a given fund. In contrast, prior studies ask whether there is a turnover-performance relation across funds. The evidence on this cross-sectional relation is mixed. For example, Elton, Gruber, Das, and Hlavka (1993) and Carhart (1997) find a negative relation, Wermers (2000), Kacperczyk, Sialm, and Zheng (2005), and Edelen, Evans, and Kadlec (2007) find no significant relation, and Dahlquist, Engström and Söderlind (2000) and Chen, Jagadeesh and Wermers (2001) find a positive relation. In accord with this mixed message, our sample delivers a cross-sectional relation that is positive but only marginally significant.

Consistent with the empirical results, our model predicts that the time-series relation between turnover and performance should be stronger than the cross-sectional relation. The reason is that a given trade's cost reduces current return, whereas its profit increases future return. Trading costs therefore do not dampen the time-series turnover-performance relation

[1]As of 2013, mutual funds worldwide have about $30 trillion of assets under management, half of which is managed by U.S. funds. About 52% of U.S. mutual fund assets are held in equity funds, and 81.6% of the equity funds' total net assets are managed actively (Investment Company Institute, 2014).

as much as they dampen the cross-sectional relation, for which the timing of profit and trading cost is irrelevant.

Our model also predicts that funds trading less-liquid stocks should have a stronger time-series relation between turnover and performance. The turnover of such funds optimally responds less to profit opportunities, so a given change in turnover implies a greater change in profit opportunities. Consistent with this prediction, we find that funds holding stocks of small companies, or small-cap funds, have a significantly stronger turnover-performance relation than do large-cap funds. Similarly, we find a stronger relation for small funds than large funds, consistent with the ability of smaller funds to trade less-liquid stocks, given that smaller funds tend to trade in smaller dollar amounts.

The model also predicts a stronger turnover-performance relation for funds that are more skilled. Intuitively, if a less-skilled fund trades on profit opportunities that are not really there, then some of the fund's turnover is unrelated to future performance. Under the plausible assumption that more-skilled funds charge higher fees, the turnover-performance relation should be stronger for more expensive funds. That is indeed what we find.

We find strong evidence of commonality in fund turnover. Turnover's common component appears to be related to mispricing in the stock market. Average turnover across funds—essentially the first principal component of turnover—is significantly related to three proxies for potential mispricing: investor sentiment, cross-sectional dispersion in individual stock returns, and aggregate stock market liquidity. Funds trade more when sentiment or dispersion is high or liquidity is low, suggesting that stocks are more mispriced when funds collectively perceive greater profit opportunities. We also find that commonality in turnover is especially high among funds sharing similar characteristics, suggesting more comovement in profit opportunities across similar funds.

Average turnover of similar funds positively predicts a fund's future return, even when we control for the fund's own turnover. This predictive relation is significant: a one-standard-deviation increase in similar funds' average turnover is associated with a 0.43% per year increase in fund performance. The relation is weaker when average turnover is computed across all funds, consistent with lesser commonality among dissimilar funds.

The predictive ability of average turnover is consistent with the presence of error in our empirical measure of an individual fund's turnover. This measure aims to exclude trades arising from a fund's inflows and outflows, thereby reflecting only trades arising from the fund's decisions to replace some stocks with others, but this objective can be accomplished only imperfectly. Due to commonality in turnover, average turnover of similar funds helps capture a fund's true turnover, thereby helping predict the fund's performance.

Average turnover should also predict returns if funds trade suboptimally in that only a portion of their trading exploits true profit opportunities. If those opportunities are correlated across funds while funds' trading mistakes are not, then higher average turnover indicates greater profit opportunities in general. Any opportunity identified by a given fund is likely to be more profitable if there is generally more mispricing at that time, as indicated by other funds' heavy trading. Our model formalizes this story. Suboptimal trading can also explain the superior predictive power of similar funds' average turnover, as that turnover reflects especially relevant profit opportunities—those shared by similar funds.

The literature investigating the skill of active mutual funds is extensive. Average past performance delivers a seemingly negative verdict, since many studies show that active funds have underperformed passive benchmarks, net of fees.[2] Yet active funds can have skill. Skilled funds might charge higher fees, and some funds might be more skilled than others. Moreover, with fund-level or industry-level decreasing returns to scale, skill does not equate to average performance, either gross or net of fees.[3]

We provide novel evidence of skill in active management. Our results indicate that funds' profit opportunities vary over time, and that funds have the ability to identify and exploit these opportunities. While others have already found evidence of skill, our focus on time variation in profit opportunities seems unique.[4] In a way, we identify a new dimension of fund skill—the ability to tell when profit opportunities are better. Our finding that funds are able to successfully time their trading activity seems new in the literature.

While we find that funds perform better after increasing their trading activity, others have related fund activity to performance in different ways. Kacperczyk, Sialm, and Zheng (2005) find that funds that are more active in the sense of having more concentrated portfolios perform better. Kacperczyk, Sialm, and Zheng (2008) find that a fund's actions between portfolio disclosure dates, as summarized by the "return gap," positively predict fund performance. Cremers and Petajisto (2009) find that funds that deviate more from their benchmarks, as measured by "active share," perform better. Cremers, Ferreira, Matos, and Starks (2016) find similar results. In the same spirit, Amihud and Goyenko (2013) find bet-

[2]See, for example, Jensen (1968), Elton, Gruber, Das, and Hlavka (1993), Malkiel (1995), Gruber (1996), Carhart (1997), Wermers (2000), Pástor and Stambaugh (2002), and Fama and French (2010), among others.

[3]See Berk and Green (2004), Pástor and Stambaugh (2012), Stambaugh (2014), Berk and van Binsbergen (2015), and Pástor, Stambaugh, and Taylor (2015).

[4]Studies reporting evidence of skill include Chen, Jegadeesh, and Wermers (2000), Cohen, Coval, and Pástor (2005), Cohen, Frazzini, and Malloy (2008), Baker et al. (2010), Kacperczyk, van Nieuwerburgh, and Veldkamp (2014), and others. Our approach and findings are quite different from those of Kacperczyk et al. who find evidence of time variation in skill over the business cycle.

ter performance among funds having lower R-squareds from benchmark regressions. These studies are similar to ours in that they also find that more-active funds perform better, but there are two important differences. First, all of these studies measure fund activity in ways different from ours. Second, all of them identify cross-sectional relations between activity and performance, whereas we establish a time-series relation.

As noted earlier, our measure of fund turnover aims to exclude trades induced by fund flows, thus capturing trades that are largely discretionary. A different approach is used by Alexander, Cici, and Gibson (2007), who classify a fund's large stock purchases (sales) concurrent with heavy fund outflows (inflows) as discretionary trades. Both approaches to capturing discretionary trading are imperfect: Ours is not completely immune to flows, while theirs includes just a subset of discretionary trades, since discretionary purchases (sales) surely also occur during inflows (outflows). The main finding of Alexander et al.—that discretionary purchases outperform benchmarks—is similar to ours in that it points to skill in funds' discretionary trading. But our study differs from theirs in two critical ways. First, we analyze time variation in the amount of discretionary trading. While Alexander et al. find that discretionary trades are profitable, we find that funds perform better in periods when they engage in more discretionary trading. Our findings indicate that funds' profit opportunities are time-varying, whereas their findings do not. More generally, our primary goal is to explore how funds trade in response to time variation in profit opportunities. This time variation underlies our key findings of the time-series turnover-performance relation and the commonality in turnover. Time variation in profit opportunities is central to our empirical strategy as well as to our theoretical model, but it is not investigated by Alexander et al. Second, we investigate how a fund's performance relates to the amount of its discretionary trading, aggregated across stocks traded by the fund. Alexander et al. instead investigate the performance of stocks experiencing discretionary trading, aggregating across funds. In other words, we relate a fund's performance to how heavily the fund trades, whereas they relate a stock's performance to how heavily funds trade it.

Given our focus on time-varying opportunities, our study is also related to the literature on time variation in mutual fund performance. Some authors, inspired by Ferson and Schadt (1996), model performance as a linear function of conditioning variables (e.g., Avramov and Wermers, 2006). Others relate fund performance to the business cycle (e.g., Moskowitz, 2000, Glode, 2011, Kosowski, 2011, and Kacperczyk, van Nieuwerburgh, and Veldkamp, 2016), to aggregate market returns (Glode, Hollifield, Kacperczyk, and Kogan, 2012), and to time variation in fund risk (e.g., Brown, Harlow, and Starks, 1996, and Huang, Sialm, and Zhang, 2011). None of these studies relate fund performance to fund turnover.

Our analysis of the common variation in fund turnover is related to the literature on correlated trading behavior of mutual funds, or "herding." Early studies include Nofsinger and Sias (1999) and Wermers (1999). More recently, Koch, Ruenzi, and Starks (2016) and Karolyi, Lee, and van Dijk (2012) argue that such correlated trading gives rise to commonality in liquidity among stocks. Commonality in individual stock turnover is analyzed by Lo and Wang (2000), Cremers and Mei (2007), and others. None of these studies examine fund turnover. Our analysis of the common component of fund turnover is novel.

The rest of the paper is organized as follows. Section I presents our model, which implies a positive relation between a fund's turnover and subsequent return. Section II reports strong evidence of such a relation in our mutual fund sample and, in the context of our model, contrasts the time-series relation with the weaker cross-sectional relation. Section III explores differences in the strength of the time-series relation across categories of funds differentiated by size, fees, and investment styles. Section IV analyzes the common component of fund turnover and its predictive power for fund returns. Section V concludes.

I. Model of the Turnover-Performance Relation

In this section we present a simple model of optimal fund turnover in the presence of time-varying profit opportunities. A manager trades more when he identifies more alpha-producing opportunities, so a skilled manager should perform better after he trades more. The model implies a positive turnover-performance relation: a time-series regression in which a fund's turnover is positively related to the fund's subsequent return.

A. Profit Opportunities and Trading Costs

Active mutual funds pursue alpha—profit in excess of their benchmarks. A fund perceives opportunities for producing alpha and trades to exploit them. Let X_t denote a given level of turnover that the fund can choose in period t. Let $P(X_t)$ denote the resulting expected benchmark-adjusted profit (alpha) in period $t+1$, before fees and trading costs, if the fund makes optimal buy-sell decisions conditional on its turnover being X_t. The profit represented by $P(X_t)$ reflects the fund's ability to exploit opportunities in period t for which the payoff occurs in period $t+1$. A prime example is a purchase of underpriced securities in period t followed by the correction of the mispricing in period $t+1$.

If the fund wishes to maintain a well diversified portfolio of stocks, the fund is likely to replace more of its stocks when X_t is high than when X_t is low. As the fund moves further down its list of potential stocks to buy, the alphas on the additional stocks are likely to be lower than those on stocks higher up the fund's list. As a result, $P(X_t)$ is likely to be concave in X_t. We represent this concave profit function as

$$P(X_t) = \pi_t X_t^{1-\theta}, \tag{1}$$

where $0 < \theta < 1$. Variation over time in the fund's profit opportunities is summarized by the parameter $\pi_t \geq 0$. The higher is π_t, the more profitable are the fund's opportunities.

Let $C(X_t)$ denote the trading cost in period t incurred by the fund as a result of turning over X_t in that period. We represent the trading cost function as

$$C(X_t) = cX_t^{1+\gamma}, \tag{2}$$

where $\gamma \geq 0$ and $c > 0$. We allow this function to be convex because it is generally accepted that the cost of trading a given stock is convex in the amount of that stock traded (e.g., Kyle and Obizhaeva (2013)). To the extent that a higher value of X_t corresponds to the fund trading more of any given stock, we would expect some convexity in $C(X_t)$. On the other hand, if a higher value of X_t corresponds to the fund mainly replacing a greater number of its stocks, as opposed to trading a greater amount of any given stock, then $C(X_t)$ should be close to linear. That is, γ should be close to zero. As we explain below, a near-zero value of γ is consistent with our empirical evidence on the turnover-performance relation.

B. Optimal Turnover

The fund's chosen level of turnover maximizes expected next-period profit net of the current trading cost incurred to produce that profit. We assume that the fund maximizes this after-cost profit before subtracting fees charged to investors.[5] Recall that $P(X_t)$ in equation (1) is profit before both fees and trading costs. The fund's choice of X_t therefore solves

$$\max_{X_t} \left\{ P(X_t) - C(X_t) \right\} . \tag{3}$$

This objective function is concave and hump-shaped in X_t. The first-order condition is

$$\pi_t(1-\theta)X_t^{-\theta} - c(1+\gamma)X_t^{\gamma} = 0 , \tag{4}$$

from which the optimal level of turnover is

$$X_t^* = \left[\frac{\pi_t(1-\theta)}{c(1+\gamma)} \right]^{\frac{1}{\theta+\gamma}} . \tag{5}$$

[5]This assumption is essentially equivalent to the common assumption that fund managers maximize their total fee. Since we do not model how the fee is determined—that is, how fund managers bargain with fund investors over the fund's profit—it is natural to assume that the managers maximize this profit. If the investors have no bargaining power, as in Berk and Green (2004), then they earn zero net alpha, and the managers' fee rate is equal to the fund's gross alpha. If the investors do have some bargaining power, then the managers receive only a fraction of the profit in the form of fees. But for any given positive fraction, a fee-maximizing manager wants to maximize the fund's profit.

We see that the fund trades more when its profit opportunities are better (i.e., when π_t is higher). Also, higher trading costs (c) imply less trading. Both results are intuitive.

When the fund decides how much to trade, it conditions on equilibrium prices. We do not model the formation of equilibrium prices, which reflect the joint effects of all funds' trading. Instead, we rely on a simple point: Whatever the price formation process, if equilibrium prices do not offer the fund a higher profit at the fund's chosen level of turnover than at any other level of turnover, then the fund is not optimizing. When specifying the fund's optimization problem in equation (3), we assume there are many funds and that any individual fund takes equilibrium prices—and thus its own after-cost profit opportunities—as given when deciding how much to trade. In other words, $C(X_t)$ does not represent price impact that affects the equilibrium prices on which the fund conditions. Rather, $C(X_t)$ is best viewed as compensation to liquidity-providing intermediaries for taking short-lived positions to facilitate the ultimate market clearing between the fund and other investors.[6]

C. Turnover-Performance Relation

To relate turnover to performance, we first solve equation (5) for π_t, obtaining

$$\pi_t = \frac{c(1+\gamma)}{(1-\theta)} (X_t^*)^{\theta+\gamma} \; . \tag{6}$$

Substituting for π_t into equation (1) when $X_t = X_t^*$ then gives the time-series relation

$$P(X_t^*) = \frac{c(1+\gamma)}{1-\theta} (X_t^*)^{1+\gamma} \; . \tag{7}$$

The profit and cost given by equations (1) and (2) can be viewed as being scaled by the fund's assets, so that they represent contributions to the fund's rate of return. With that normalization, the fund's overall before-fee realized return in period $t+1$, R_{t+1}, equals $P(X_t^*)$ plus a mean-zero deviation minus $C(X_{t+1}^*)$, the trading costs associated with the optimal turnover chosen in period $t+1$. That is, using equations (2) and (7),

$$R_{t+1} = \frac{c(1+\gamma)}{1-\theta} (X_t^*)^{1+\gamma} - c(X_{t+1}^*)^{1+\gamma} + \eta_{t+1} \; , \tag{8}$$

where η_{t+1} is the mean-zero deviation of realized before-cost profit from its expectation. We assume that profit opportunities vary over time in a manner that allows the conditional mean of $(X_{t+1}^*)^{1+\gamma}$ given X_t^* to be well approximated as

$$\mathrm{E}\{(X_{t+1}^*)^{1+\gamma} | X_t^*\} = \mu(1-\rho) + \rho(X_t^*)^{1+\gamma} \; , \tag{9}$$

where μ and ρ are constants and $|\rho| < 1$.[7] Taking the expectation of the right-hand side of

[6] One might imagine funds trading with many intermediaries who access different sources of liquidity or act at slightly different times. A similar approach is taken by Stambaugh (2014) in a general equilibrium model of active management and price formation.

[7] From (5), we see that a sufficient condition for this result is that $\pi_t^{\frac{1+\gamma}{\gamma+\theta}}$ follows an AR(1) process.

equation (8) conditional on X_t^* then gives

$$\mathrm{E}\{R_{t+1}|X_t^*\} = \frac{c(1+\gamma)}{1-\theta}\,(X_t^*)^{1+\gamma} - c\left[\mu(1-\rho) + \rho(X_t^*)^{1+\gamma}\right] \ . \tag{10}$$

As noted earlier, γ is likely to be close to zero if higher turnover largely corresponds to replacing a greater number of stocks rather than buying more of a given set of stocks. We see from (10) that a near-zero γ delivers a near-linear relation between turnover (X_t^*) and expected return. Our empirical analysis reveals no significant departure from linearity in the turnover-performance relation, consistent with the assumption of $\gamma \approx 0$. Given this assumption, from (9) we see that $\mu = \mathrm{E}(X_t^*)$ and ρ is the autocorrelation of X_t^*. With $\gamma \approx 0$, the turnover-performance relation in (10) is well represented by the linear regression

$$R_{t+1} = a + bX_t^* + \epsilon_{t+1} \ , \tag{11}$$

where $\mathrm{E}(\epsilon_{t+1}|X_t^*) = 0$,

$$a = -c(1-\rho)\mathrm{E}(X_t^*), \tag{12}$$

and

$$b = c\left(\frac{1}{1-\theta} - \rho\right) \ . \tag{13}$$

Note that b is positive because $0 < \theta < 1$ and $|\rho| < 1$. In other words, a fund's optimally chosen turnover exhibits a positive time-series relation to the fund's subsequent return.

D. Time-Series versus Cross-Section

Most studies investigating the relation between fund turnover and performance focus on the cross-section. The question generally asked is whether there is a relation, across funds, between average turnover and average return. Taking the unconditional expectation of the time-series relation in equation (11), using equations (12) and (13), gives

$$\mathrm{E}(R_t) = h\,\mathrm{E}(X_t^*) \ , \tag{14}$$

where

$$h = \frac{c\,\theta}{1-\theta} \ . \tag{15}$$

If c and θ are the same across funds, then h is the same for each fund. In that case, equation (14) represents the relation between average turnover and average performance across funds. From equation (5) we see that funds typically experiencing higher values of π_t, and thus greater profit opportunities, trade more and thus have higher values of $\mathrm{E}(X_t^*)$. From (14), this higher average turnover is accompanied by higher return, because the slope in the cross-sectional relation, h, is positive (recalling $0 < \theta < 1$). However, this cross-sectional slope is lower than the slope of the time-series relation, b. Specifically, from equations (13) and (15),

$$b - h = c(1-\rho) \ , \tag{16}$$

which is positive. The time-series slope is greater because trading costs associated with turnover do not subtract from the fund's return in the same period as the profit resulting from that turnover. In contrast, the timing of profit and trading cost is irrelevant for the cross-sectional relation. Trading costs therefore weaken the time-series turnover-performance relation by less than they weaken the cross-sectional relation. The empirical results in Section II are consistent with the model's implied difference between the time-series and cross-sectional slopes, given in equation (16).

E. Suboptimal Trading

Our model above assumes that funds trade optimally, but we also extend the model to a setting in which they do not. When a fund trades suboptimally, its turnover in period t, X_t, produces less than the maximized value of expected profit in equation (3). We assume the fund's expected profit is instead equal to δ times that maximized value, where $\delta \leq 1$. In this sense, δ reflects the fund's skill in exploiting its profit opportunities, with maximal skill (optimal trading) corresponding to $\delta = 1$. We also assume that the fund's turnover under optimal trading, X_t^*, is on average equal to its actual turnover, X_t, and that the latter by itself is not informative about the fund's skill, δ.

Details of this model extension are provided in the Appendix. Here we summarize the main implications. First, the lower is a fund's skill, the weaker is its turnover-performance relation. The relation one expects to observe in a pooled fund universe is given by

$$\mathrm{E}(R_{t+1}|X_t) = \bar{a} + \bar{b}X_t \ , \tag{17}$$

where

$$\begin{aligned} \bar{a} &= -c(1-\rho)\mathrm{E}(X_t) \qquad (18) \\ \bar{b} &= c\left[\frac{1-\theta(1-\bar{\delta})}{1-\theta} - \rho\right] \ , \qquad (19) \end{aligned}$$

and $\bar{\delta}$ is the mean δ across funds. The lower is this average level of skill, the weaker is the time-series turnover-performance relation, i.e., the lower is $\bar{b}$. Similarly, the cross-sectional turnover-performance slope is lowered by suboptimal trading. That relation now becomes

$$\mathrm{E}(R_t) = \bar{h}\,\mathrm{E}(X_t) \ , \tag{20}$$

where

$$\bar{h} = \frac{\bar{\delta}\,c\,\theta}{1-\theta} \ , \tag{21}$$

so that $\bar{h}$ is increasing in $\bar{\delta}$. In the optimal-trading setting where $\bar{\delta} = 1$ and $X_t = X_t^*$ for each fund, the values of $\bar{a}$, $\bar{b}$, and $\bar{h}$ are equal to those in equations (12), (13), and (15), respectively. Note, however, that

$$\bar{b} - \bar{h} = c(1 - \rho) \ , \tag{22}$$

which is positive and equal to $b - h$ in equation (16). In other words, suboptimal trading lowers both the time-series and cross-sectional slopes, but the difference between them is unaffected. The time-series turnover-performance relation is thus stronger than the cross-sectional relation regardless of $\bar{\delta}$, the average level of skill among funds.

The average level of skill does affect the strength of the turnover-performance relation, including its sign. From equations (19) and (21), the cross-sectional relation is positive when $\bar{\delta} > 0$, and the time-series relation is positive when $\bar{\delta}$ exceeds $(\rho - 1)(1 - \theta)/\theta < 0$. But if $\bar{\delta}$ is sufficiently negative, so are both turnover-performance relations. This is intuitive—if funds are so unskilled that they are expected to lose money when they trade, then more trading implies weaker performance. This scenario seems unlikely for most professional fund managers, but it could very well describe households. For example, Barber and Odean (2000) show that households that trade more earn lower returns, consistent with $\bar{\delta} < 0$. As long as funds are skilled enough so that $\bar{\delta} > 0$, the turnover-performance relation is positive in both the time series and the cross section, consistent with the empirical evidence we present next.

II. Estimating the Turnover-Performance Relation

Following equation (11), we specify the time-series turnover-performance relation for a given fund i as the linear regression

$$R_{i,t} = a_i + b_i X_{i,t-1} + \epsilon_{i,t} \ , \tag{23}$$

where $R_{i,t}$ is the fund's benchmark-adjusted return in period t, and $X_{i,t-1}$ is the fund's turnover in period $t - 1$. As implied by our model, a positive b_i reflects the fund's skill to identify and trade on opportunities in period $t-1$ for which a significant portion of the payoff occurs in period t. One can imagine other forms of skill, outside of the model, that we would not detect. For example, a fund could have skill to identify short-horizon opportunities, such as liquidity provision, that deliver all of their profits in period $t - 1$.[8] Or a fund could identify only long-horizon opportunities that bear fruit after period t. Moreover, detecting skill using the turnover-performance relation requires time variation in the extent to which

[8] In the presence of skill, a higher $X_{i,t-1}$ can contribute positively to both $R_{i,t-1}$ and $R_{i,t}$. Thus, one might also look for a positive contemporaneous relation between turnover and return. Such a relation, however, could simply reflect a manager's trading in reaction to return, thereby confounding an inference about skill. We therefore focus on the predictive turnover-performance relation in equation (23).

profit opportunities arise, i.e., variation in π_t in equation (1). Although the regression in equation (23) cannot detect all forms of skill, it nevertheless provides novel insights into the ability of funds to identify and exploit time-varying profit opportunities.

We explore the turnover-performance relation using the dataset constructed by Pástor, Stambaugh, and Taylor (2015), who combine CRSP and Morningstar data to obtain a sample of 3,126 actively managed U.S. domestic equity mutual funds covering the 1979–2011 period. To measure the dependent variable $R_{i,t}$, we follow the above study in using the fund's net return minus the return on the benchmark index designated by Morningstar, plus the fund's monthly expense ratio taken from CRSP. Following our model, we use gross return, i.e., the return before fees charged to investors. We estimate all regressions at a monthly frequency, but a fund's turnover is reported only as the total for its fiscal year. Thus, we measure turnover, $X_{i,t-1}$, by the variable $FundTurn_{i,t-1}$, which is the fund's turnover for the most recent fiscal year that ends before month t. This measure is defined as

$$FundTurn_{i,t-1} = \frac{\min\left(buys_{i,t-1}, sells_{i,t-1}\right)}{\text{avg}\left(TNA_{i,t-1}\right)} \ , \tag{24}$$

where the numerator is the lesser of the fund's total purchases and sales over its most recent fiscal year that ends before month t, and the denominator is the fund's average total net asset value over the same 12-month period. We have no discretion over this definition; this is the measure of turnover that funds are required to report to the SEC, and it is also the measure provided by CRSP. We discuss some properties of this measure later in Section II.B.1. We winsorize $FundTurn_{i,t-1}$ at the 1st and 99th percentiles.

To increase the power of our inferences in equation (23), we estimate a panel regression that imposes the restriction

$$b_1 = b_2 = \cdots = b \ . \tag{25}$$

Initially we pool across all funds, and then later we pool within various fund categories when investigating heterogeneity in the turnover-performance relation. We include fund fixed effects, so that b reflects only the contribution of within-fund time variation in turnover. The fund fixed effects correspond to the a_i's in equation (23) when the restriction in (25) is imposed across all funds. The regression specification combining equations (23) and (25), which isolates the time-series relation between turnover and performance, is our main specification. For comparison, we also consider other specifications, as we explain next.

A. *Time-series versus Cross-Sectional Estimates*

Table I reports the estimated slope coefficient on turnover, or $\widehat{b}$, for various specifications of the panel regression capturing the turnover-performance relation. The top left cell reports

$\widehat{b}$ from our main specification, which combines equations (23) and (25):

$$R_{i,t} = a_i + bX_{i,t-1} + \epsilon_{i,t} \ . \tag{26}$$

This specification includes fund fixed effects, so the OLS estimate $\widehat{b}$ reflects only time-series variation in turnover and performance. This statement emerges clearly from the fact that, with fund fixed effects, $\widehat{b}$ is a weighted average across funds of the slope estimates from fund-by-fund time-series regressions. The weighting scheme places larger weights on the time-series slopes of funds with more observations as well as funds whose turnover fluctuates more over time. See the Appendix for details.

******************* INSERT TABLE I HERE *******************

The estimate $\widehat{b}$ in the top left cell of Table I is positive and highly significant, with a t-statistic of 6.67. This finding of a positive turnover-performance relation in the time series is the main empirical result of the paper. The relation is significant not only statistically but also economically. The average within-fund standard deviation of $X_{i,t-1}$ is 0.437. Therefore, the estimated slope of 0.00125 implies that a one-standard-deviation increase in a fund's turnover translates to an increase in annualized expected return of 0.66% (= $0.00125 \times 0.437 \times 1200$). This number is substantial, in that it exceeds funds' overall average annualized $R_{i,t}$, equal to 0.47%. In other words, conditioning fund returns on turnover implies fluctuations in the conditional expected return that are of first-order economic importance, often larger than the unconditional expected return.

The top right cell of Table I reports $\widehat{b}$ from a panel regression that includes both fund and month fixed effects. The resulting estimate, 0.00118, is only slightly smaller than its counterpart in the top left cell, and it is similarly significant ($t = 7.08$). The only difference from the top left cell is the addition of month fixed effects. This addition controls for any unobserved variables that change over time but not across funds, such as macroeconomic variables, regulatory changes, and aggregate trading activity. Since the results with and without month fixed effects are so similar, such aggregate variables cannot explain the positive relation between turnover and performance.

The bottom left cell reports $\widehat{b}$ when no fixed effects are included in the panel regression. This specification imposes not only the restriction (25) but also

$$a_1 = a_2 = \cdots = a \ . \tag{27}$$

By removing fund fixed effects from our main specification, this additional restriction brings cross-sectional variation into play when estimating b. The estimate $\widehat{b}$ in the bottom left cell of Table I thus reflects both cross-sectional and time-series variation. The estimate, 0.00043, is positive, with a t-statistic of 2.05.

The bottom right cell of Table I reports $\widehat{b}$ from a purely cross-sectional specification, in which fund fixed effects a_i are replaced by month fixed effects a_t:

$$R_{i,t} = a_t + bX_{i,t-1} + \epsilon_{i,t} \ . \tag{28}$$

The OLS estimate $\widehat{b}$ from this panel regression reflects only cross-sectional variation in turnover and performance. To see this, note that including month fixed effects makes $\widehat{b}$ equal to a weighted average across periods of the slope estimates from period-by-period cross-sectional regressions of performance on turnover. The weighting scheme places larger weights on periods with more observations and periods in which the independent variable exhibits more cross-sectional variance. If each period receives the same weight, then this panel regression produces the same slope coefficient as the well known Fama-Macbeth (1973) estimator. (See the Appendix.) The estimate of b from equation (28), 0.00039, is positive, with a t-statistic of 2.04. The point estimate is smaller than in the bottom left cell, which shows that isolating cross-sectional variation slightly weakens the turnover-performance relation.

Table I shows that the turnover-performance relation is stronger in the time series than in the cross section. This result is predicted by our model, according to which the difference between the time-series and cross-sectional slopes is positive and given by equation (16). (Moreover, this difference is unchanged in a framework with suboptimal trading, as shown in equation (22).) In fact, the difference between the two slopes in Table I is roughly in line with equation (16), given estimates of ρ and c. For ρ, we take the average autocorrelation of $FundTurn_{i,t-1}$, which is equal to 0.507. For c, we turn to Edelen, Evans, and Kadlec (2013), who report that, on average, the equity mutual funds in their sample have annual turnover of 82.4% and incur 1.44% of fund value annually in trading costs. The implied value of c is then $0.0144/0.824 = 0.0175$. From equation (16), the difference between the time-series and cross-sectional slopes is then equal to $c(1-\rho) = 0.0175(1-0.507) = 0.0086$. Given that ρ and c are annual quantities, this value is the implied difference in slopes when annual return is regressed on annual turnover. Table I instead reports slopes for monthly return regressed on 12-month turnover. Multiplying the latter slopes by 12 puts them roughly on a 12-month basis. Subtracting the cross-sectional slope in the lower-right cell of Table I from the time-series slope in the upper-left cell, multiplying by 12, gives $12(0.00125 - 0.00039) = 0.0103$, which rounds to 0.01, just like the above implied difference of 0.0086.[9]

[9] The time-series and cross-sectional slopes when 12-month return is regressed on 12-month turnover equal 0.0200 and 0.0118, as reported in the online appendix. The difference in these slopes, 0.0082, is also quite close to the above implied difference of 0.0086.

In sum, consistent with our model in which fund managers identify and exploit time-varying profit opportunities, a fund's performance exhibits a positive relation to the fund's lagged turnover. The turnover-performance relation is positive in both the time series and the cross-section, as predicted by the model. As the model also predicts, the time-series relation is stronger than the cross-sectional relation. Moreover, the magnitude of the difference between the time-series and cross-sectional slopes conforms well to the model.

B. Robustness

The positive time-series turnover-performance relation, which is our main result, is robust to a variety of specification changes. We summarize the robustness results here and report them in detail in the online appendix, which is available on our websites.

We have already shown that the turnover-performance relation obtains whether or not month fixed effects are included in the panel regression, which rules out all aggregate variables as the source of this relation. Furthermore, the relation obtains when we include benchmark-month fixed effects, ruling out any variables measured at the benchmark-month level.[10] An example of such a variable is benchmark turnover, which can be reflected in a fund's turnover to the extent that some of the fund's trading passively responds to reconstitutions of the fund's benchmark index. Adding benchmark-month fixed effects has a tiny effect on the estimated turnover-performance relation, strengthening our interpretation of this relation as being driven by skilled active trading. The relation also obtains, and is equally strong, when gross fund returns are replaced by net returns.

Importantly, the positive turnover-performance relation does *not* obtain in a placebo test in which we replace active funds by passive index funds, as identified by Morningstar. When we produce the counterpart of Table I for the universe of passive funds, we find no slope coefficient significantly different from zero. In fact, the estimated slope coefficients in the specifications with fund fixed effects are not even positive (the corresponding t-statistics in the top row of Table I are -0.36 and -1.02). This result is comforting because passive funds should not exhibit any skill in identifying time-varying profit opportunities. The fact that the turnover-performance relation emerges for active funds but not passive funds supports our skill-based interpretation of this relation.

If a fund's turnover is negatively correlated with the fund's contemporaneous or lagged return, then a finite sample tends to produce a positive sample correlation between return and lagged turnover even if this correlation's true value is zero. This bias, essentially the same

[10]Gormley and Matsa (2014), among others, advocate the use of a fixed-effects estimator as a way of controlling for unobserved group heterogeneity in finance applications.

as analyzed by Stambaugh (1999), arises because the sample's relatively high (low) turnover values tend to be accompanied by the sample's low (high) current and past returns. Those high (low) turnover values thus tend to precede the sample's relatively high (low) returns, thereby producing an apparent positive relation between return and lagged turnover. We find that the correlations between turnover and both contemporaneous and lagged return are negative but statistically insignificant. We nevertheless conduct a simulation analysis to gauge the potential magnitude of the bias as well as the effectiveness of a simple remedy in our setting—adding $R_{i,t-1}$ and $R_{i,t-2}$ as independent variables to the regression in equation (26). The simulation reveals that the finite-sample bias is very small and that adding the lagged returns is nevertheless effective in eliminating it. When we add $R_{i,t-1}$ and $R_{i,t-2}$ to the regression in (26), the resulting slope on $X_{i,t-1}$ and its t-statistic barely change.

We estimate the turnover-performance relation at the monthly frequency. Even though funds report their turnover only annually, most of the variables used in our subsequent analysis, such as fund returns, fund size, sentiment, volatility, liquidity, and business-cycle indicators, are available on a monthly basis. Therefore, we choose the monthly frequency in an effort to utilize all available information. Nonetheless, when we reestimate the turnover-performance relation by using annual fund returns, we find a positive and highly significant time-series relation, just like in Table I. In addition, we consider a specification that allows the slope coefficient from the monthly turnover-performance regression to depend on the number of months between the end of the 12-month period over which $FundTurn$ is measured and the month in which the fund return is computed. Specifically, we add a term to the right-hand side of the regression that interacts the above number of months with $FundTurn$. We find that the interaction term does not enter significantly, suggesting that our constant-slope specification is appropriate.

To judge the statistical significance of the turnover-performance slope estimates in the presence of fund fixed effects, we compute standard errors clustered by sector times month, where sector denotes a Morningstar style category. We choose this approach because there is mild correlation between benchmark-adjusted fund returns within the same sector but very little across sectors. For robustness, we also consider stricter clustering schemes, namely, by month, and by fund and month, and continue to find significant results.[11]

Our turnover-performance relation captures the predictive power of $FundTurn$ in a given fiscal year for fund performance in the following fiscal year (e.g., turnover in 2014 predicts

[11] In turnover-performance regressions that exclude fund fixed effects, we cluster not only by sector times month but also by fund, to account for potential residual correlation induced by the exclusion of fund fixed effects. In subsequent regressions with $FundTurn$ as the dependent variable, we cluster by fund, since $FundTurn$ is highly persistent, and by year, to allow cross-sectional dependence in $FundTurn$.

returns in 2015). In principle, some fund trades could take longer to play out (e.g., a trade in 2014 could lead to profits in 2016).[12] To test for such long-horizon effects, we add two more lags of $FundTurn$ to the right-hand side of regression (26). We find that neither of those additional lags has any predictive power for returns after controlling for the most recent value of $FundTurn$, which retains its positive and significant coefficient. Therefore, we use only the most recent $FundTurn$ in the rest of our analysis.

Our results are not driven by manager changes. When we replace fund fixed effects by fund-manager fixed effects, the results are very similar. The turnover-performance relation thus holds not only at the fund level but also at the manager level. One implication is that our results are not driven by portfolio turnover during manager transitions. In addition, our results easily survive the addition of controls for manager age and manager tenure.

We run a linear turnover-performance regression. Besides its natural simplicity, the linear specification is motivated by our model. Recall that if the trading cost function is approximately linear ($\gamma \approx 0$), so is the turnover-performance relation (see equation (11)). In principle, the relation could also be convex (if $\gamma > 0$), but we find no such evidence. We estimate a nonparametric regression of $R_{i,t}$ on $X_{i,t-1}$, both demeaned at the fund level. We find that the fitted values from that regression are remarkably close to linear, providing support for our regression specification in equation (26).

The positive turnover-performance relation emerges not only from the panel regression in Table I, which imposes the restriction (25), but also from fund-by-fund regressions. For each fund i, we estimate the slope b_i from the time-series regression in equation (23) in the full sample. We find that 61% of the OLS slope estimates $\widehat{b}_i$ are positive. Moreover, 9% (4%) of the $\widehat{b}_i$'s are significantly positive at the 5% (1%) confidence level. A weighted average of these $\widehat{b}_i$'s appears in the top left cell of Table I, as shown in equation (B15).[13] Apart from this brief summary, we do not analyze the $\widehat{b}_i$ estimates because their precision is generally low given the funds' relatively short track records. Instead, we focus on the panel-regression estimate of b whose precision is higher thanks to information-pooling across funds. The panel-regression slope characterizes the typical fund-month observation, rather than the typical fund. Therefore, we do not find that the typical fund exhibits a positive turnover-performance relation. Rather, we find that the typical fund-month exhibits a positive relation, which implies that there must exist some funds that exhibit a positive relation.

[12]The relations between fund performance and funds' investment horizons are analyzed by Yan and Zhang (2009), Cremers and Pareek (2016), and Lan, Moneta, and Wermers (2015), among others.

[13]The cross-sectional correlation between $\widehat{b}_i$ and the length of fund i's track record is insignificant at 0.01, indicating that the turnover-performance relation is no stronger for longer-lived funds.

Mutual funds sometimes benefit from receiving allocations of shares in initial public offerings (IPOs) at below-market prices. Lead underwriters tend to allocate more IPO shares to fund families from which they receive larger brokerage commissions (e.g., Reuter, 2006). To the extent that higher commissions are associated with higher turnover, this practice could potentially contribute to a positive turnover-performance relation. This contribution is unlikely to be substantial, though. Fund families tend to distribute IPO shares across funds based on criteria such as past returns and fees rather than turnover (Gaspar, Massa, and Matos, 2006). In addition, the high commissions that help families earn IPO allocations often reflect an elevated commission rate rather than high family turnover, and they are often paid around the time of the IPO rather than over the previous fiscal year.[14] Moreover, the contribution of IPO allocations to fund performance seems modest. For each year between 1980 and 2013, we calculate the ratio of total money left on the table across all IPOs, obtained from Jay Ritter's website, to total assets of active domestic equity mutual funds, obtained from the Investment Company Institute. This ratio, whose mean is 0.30%, exceeds the contribution of IPO allocations to fund performance because mutual funds receive only about 25% to 41% of IPO allocations, on average.[15] IPOs thus boost average fund performance by only about 7.5 to 12 basis points per year. Furthermore, the IPO market has cooled significantly since year 2000. Money left on the table has decreased to only 0.10% of fund assets on average, so that IPOs have boosted average fund performance by only 2.5 to 4 basis points per year since January 2001. Yet the turnover-performance relation remains strong during this cold-IPO-market subperiod: the slope estimates in the top row of Table I remain positive and significant. For example, the fund-fixed-effect-only estimate is 0.00072, which is lower than its full-sample counterpart of 0.00125 from Table I, but it remains highly significant ($t = 3.47$).

If we were to redefine our dependent variable from fund returns to dollar value added (Berk and van Binsbergen, 2015), the results would be very similar, by the following logic. When the dependent variable is dollar value added, the independent variable should be turnover in dollars. Making these changes amounts to multiplying both sides of our current regression by fund size. The new regression suffers from a heteroskedasticity problem, because larger funds have more-volatile (dollar) residuals. Adjusting for this heteroskedasticity requires down-weighting larger funds, for example, by dividing both sides of the new regression by fund size. After this division, we are back to our current regression.

We report all of our results based on the full sample period of 1979–2011. In addition, we verify the robustness of our results in the 2000–2011 subperiod, motivated by two potential

[14]See, for example, Nimalendran, Ritter, and Zhang (2007) and Goldstein, Irvine, and Puckett (2011).

[15]These estimates are from Reuter (2006), Ritter and Zhang (2007), and Field and Lowry (2009).

structural changes in the data. The first change relates to the way CRSP reports turnover. Prior to September 1998, all funds' fiscal years are reported as January–December, raising the possibility of inaccuracy, since after 1998 the timing of funds' fiscal years varies across funds.[16] The second change, identified by Pástor, Stambaugh, and Taylor (2015), relates to the reporting of fund size and expense ratios before 1993. Using the 2000–2011 subperiod provides a robustness check that is conservative in avoiding both potential structural changes. We find that our main conclusions are robust to using the 2000–2011 subperiod. For example, the time-series turnover-performance relation in Table I remains positive and significant, with slope estimates of 0.00101 ($t = 4.29$) and 0.00084 ($t = 4.09$) in the top row. In the online appendix, we report all of our tables reestimated in the 2000–2011 subperiod.

B.1. Measuring Turnover

We measure fund turnover by its official SEC definition from equation (24). One advantage of this measure is that, by taking the minimum of purchases and sales, it largely excludes turnover arising from persistent inflows and outflows to and from the fund. For example, if a fund experiences inflows throughout the year, it will probably use those inflows to buy stocks, but the SEC turnover will pick up the fund's sales, which are not driven by flows. Similarly, if a fund experiences persistent outflows, there will be flow-driven selling, but our turnover measure will pick up the fund's purchases. Since fund flows are well known to be persistent, our turnover measure is largely immune to flows. Instead, it reflects mostly the fund's active portfolio decisions to replace some holdings with others.

Our turnover measure is not completely immune to fund flows, though. If flows are non-persistent then some of our turnover is flow-driven. Flow-driven trading is fairly mechanical in that its timing is determined mostly by the fund's investors rather than the fund's manager. Therefore, flow-driven turnover should exhibit a weaker relation to fund performance than our turnover measure, $FundTurn$. To test this hypothesis, we construct two measures of flow-driven fund turnover. Both measures rely on monthly dollar flows, which we back out from the monthly series of fund size and fund returns, and both cover the same 12-month period as $FundTurn$. The first measure is the sum of the absolute values of the 12 monthly dollar flows, divided by the average fund size during the 12-month period. The second measure is the smaller of two sums, one of all positive dollar flows and one of all negative flows during the 12-month period, divided by average fund size. Consistent with our

[16]In private communication, CRSP explained that this change in reporting is related to the change in its fund data provider from S&P to Lipper on August 31, 1998. CRSP has also explained the timing convention for turnover, which is the variable *turn_ratio* in CRSP's *fund_fees* file. If the variable *fiscal_yearend* is present in the file, turnover is measured over the 12-month period ending on the *fiscal_yearend* date; otherwise turnover is measured over the 12-month period ending on the date marked by the variable *begdt*.

hypothesis, we find that neither measure of flow-driven turnover has any predictive power for fund returns, whether or not we include $FundTurn$ as a control. Moreover, the inclusion of flow-driven turnover does not affect the significant predictive power of $FundTurn$. Finally, when we adjust our turnover measure for flows by subtracting flow-driven turnover from $FundTurn$, we find that the difference strongly predicts fund performance. All these results provide additional support for our interpretation of the turnover-performance relation.

In our final test related to fund flows, we calculate their time-series volatility, which could in principle be related to the time variation in fund turnover. We compute flow volatility for each fund as the standard deviation of the fund's 12 monthly net flows during the same period over which $FundTurn$ is measured. When we add flow volatility as a control in our turnover-performance regression, the control does not enter significantly and the slope on $FundTurn$ remains very similar and highly significant.

In addition to fund flows, some portion of turnover could be driven by other non-discretionary forces such as manager transitions, benchmark index reconstitutions, portfolio rebalancing, etc. Turnover driven by manager transitions cannot explain our results because those hold up when we replace fund fixed effects by manager fixed effects, as noted earlier. Benchmark index reconstitutions cannot explain our results either because those survive the inclusion of benchmark-month fixed effects, as explained earlier. Another way to account for benchmark index turnover is to estimate it from the turnover of index funds tracking the fund's benchmark. For each active fund, we calculate benchmark-adjusted turnover as $FundTurn$ minus the median turnover of all index funds in the same Morningstar category, measured over the same period as $FundTurn$. When we replace $FundTurn$ by its benchmark-adjusted version, we continue to find a positive and highly significant turnover-performance relation.

Regardless of its source, any trading unrelated to profit motive widens the gap between a fund's turnover and its optimal turnover in the context of our model. Therefore, any such trading should make it more difficult for us to find a positive turnover-performance relation. Yet we do find a strong relation, even without adjusting reported turnover for non-discretionary trading. It is possible that some adjustment could enhance the predictive power of SEC turnover, but it is not our goal to find the best predictor of fund returns. For simplicity, we use the SEC turnover measure throughout our main analysis.

For robustness, we consider one more modification of our turnover measure. The denominator of our measure is average fund size over the previous fiscal year. To see whether this averaging somehow influences our results, we rescale our turnover measure by the ratio of the same average fund size to fund size at the beginning of the previous fiscal year. The denominator of the turnover measure thus changes from average size to fund size at the beginning of the previous fiscal year. We find that this rescaled turnover measure predicts performance even more strongly than our standard SEC measure.

Even though we analyze equity mutual funds, some of the funds' turnover could be due to non-equity assets. To see whether non-equity turnover matters, we obtain data from Morningstar on the percentage of each fund's assets invested in stock. When we add this percentage as a control in our turnover-performance regression, it enters with a small positive coefficient, but the explanatory power of $FundTurn$ is virtually unchanged.

B.2. Alternative Benchmark Models

We benchmark each fund's performance against the index selected for the fund's category by Morningstar. For example, for small-cap value funds, the benchmark is the Russell 2000 Value Index; for large-cap growth funds, it is Russell 1000 Growth. There is a one-to-one mapping between benchmarks and style categories. Morningstar assigns funds to style categories based on the funds' reported portfolio holdings, and it updates these assignments over time. Since the assignments are made by Morningstar rather than by funds themselves, there is no room for benchmark manipulation of the kind documented by Sensoy (2009). The benchmark assigned by Morningstar can differ from that reported in the fund's prospectus.

Our index-based approach is likely to adjust for fund style and risk more precisely than the commonly used loadings on the three Fama-French factors. The Fama-French factors are popular in mutual fund studies because their returns are freely available, unlike the Morningstar benchmark index data. Yet the Fama-French factors are not obvious benchmark choices because they are long-short portfolios whose returns cannot be costlessly achieved by mutual fund managers. Moreover, Cremers, Petajisto, and Zitzewitz (2013) argue that the Fama-French model produces biased assessments of fund performance, and they recommend using index-based benchmarks instead. We follow this advice. But we find similar results when we adjust fund returns by using the three Fama-French factors: the slope coefficients in the top row of Table I continue to be highly significant, with t-statistics of 7.09 and 8.27. We also find similar results when using three additional alternative benchmark models: the four-factor model that includes the three Fama-French factors and momentum, the five-factor model of Fama and French (2015), and the modified Fama-French three-factor model of Cremers, Petajisto, and Zitzewitz (2013). In all three cases, our main slope coefficients in the top row of Table I continue to be highly significant, with t-statistics ranging from

5.93 to 9.34. The cross-sectional turnover-performance relation is less robust to the choice of benchmark. It remains significant when we use the Fama-French five factors or Cremers-Petajisto-Zitzewitz factors, for which the t-statistics range from 2.05 to 3.71, but it becomes statistically insignificant when we use the other benchmarks.

We assess fund performance by subtracting Morningstar's designated benchmark return from the fund's return, effectively assuming that the fund's benchmark beta is equal to one. This simple approach is popular in investment practice, and it circumvents the need to estimate the funds' betas. When we estimate those betas using OLS, we find very similar results. To avoid using imprecise beta estimates for short-lived funds, we replace OLS betas of funds having track records shorter than 24 months by the average beta of funds in the same Morningstar category. Just as in Table I, we find that the slopes in the top row are highly significant, with t-statistics close to 7.6. The slopes in the bottom row are marginally insignificant, with t-statistics of 1.7. These results underline our earlier finding that the time-series turnover-performance relation is stronger than the cross-sectional one.

The tests described above assume that funds' betas are time-invariant. In separate tests, we allow funds' betas on benchmarks or factors to vary over time in order to assess the extent to which turnover-related performance might reflect variation in systematic risk. If high turnover were associated with more systematic risk, then the higher returns following high turnover could represent risk compensation or simply factor timing—identifying factor-related mispricing. While it is not clear a priori why higher turnover should be followed by more as opposed to less systematic risk, we nevertheless allow time variation in funds' betas on their Morningstar benchmarks and the factors in the four alternative factor models described above. In those results, the turnover-performance relation weakens only modestly, suggesting that relation might include some risk compensation or factor timing. In all cases, however, the t-statistic for the slope on turnover exceeds five. In general, turnover can reflect various sources of profitable trading—stock picking, industry rotation, factor timing, etc.

B.3. Out-of-Sample Evidence

Our regression evidence is based on the full sample. While full-sample regressions are suitable for testing our model's predictions, an investor might want to know whether turnover can predict fund performance out of sample. We conduct an out-of-sample analysis in this subsection, shedding more light on the strength of the turnover-performance relation.

Each month starting with January 1984 (i.e., five years after the beginning of our sample), we estimate two panel regressions of $R_{i,t}$ on fund fixed effects, using historical data only.

The first regression includes just fund fixed effects, while the second regression also includes $FundTurn_{i,t-1}$. Proceeding sequentially month by month, we obtain the times series of out-of-sample forecasts from both regressions, as well as the series of the slope estimates on $FundTurn_{i,t-1}$ from the second regression.

We find that the time series of those slope estimates is fairly stable over time.[17] The turnover-performance slope is always positive, ranging from 0.0005 to 0.0021 over the whole sample. (The slope's final value, 0.00125, appears in Table I.) The slope is statistically significant in all samples ending in 1996 or later. Importantly, the second regression produces better out-of-sample forecasts of fund performance. In other words, adding $FundTurn_{i,t-1}$ to the first regression reduces the average squared forecast error. This reduction is modest in magnitude but statistically significant (t=2.63). Fund turnover thus helps predict fund performance even when using real-time information.

III. Differences Across Funds

Our evidence so far reveals that the typical fund performs better after it trades more. Next, we ask whether this time-series relation differs across funds. We distinguish funds along four characteristics: fund size, expense ratio (or "fee," for short), and two common style classifications—small-cap versus large-cap and value versus growth. For each of these four characteristics, we assign a fund to one of three categories. For fund size and fee, in each month t we compute the terciles of $FundSize_{i,t-1}$ and $ExpenseRatio_{i,t-1}$, the most recent values of fund i's assets under management and fees available from CRSP prior to month t. For the two style classifications, we use the 3×3 "style-box" assignments of Morningstar, which uses a fund's holdings to classify the fund as (i) small-cap, mid-cap, or large-cap and (ii) value, blend, or growth.

******************* INSERT TABLE II HERE *******************

Panels A through D of Table II report the estimated slope coefficients on turnover for each of the four characteristics used to classify funds. Each panel reports two sets of regressions. In the first set (indicated by "Controls" as "No"), the simple regression in equation (26) is run without additional control variables. The second set of regressions (with "Controls" as "Yes") controls for the other three fund characteristics by including category dummies interacted with lagged turnover. For the latter regressions, the slopes reported in each panel should be interpreted as applying to a fund falling in the given category of that panel's

[17]The plot of the time series is available in the online appendix, along with more details.

characteristic and having middle-category values of the characteristics in the other three panels. For example, the slopes in Panel A correspond to a blend fund with medium size and medium expense ratio.

Table II reveals a significantly positive turnover-performance relation in eleven of the twelve no-controls regressions. The only exception is large funds, having a t-statistic of 1.24 (Panel C, third column). In other words, a positive turnover-performance relation is quite pervasive across the various subsets of funds produced by the four classifications.

We also see in Table II that turnover-performance slopes are significantly larger for small-cap funds as compared to large-cap funds (Panel A), small funds as compared to large funds (Panel C), and high-fee funds as compared to low-fee funds (Panel D). These significant differences occur in both the no-controls and with-controls results, and they are rather dramatic. For example, in the with-control results, small-cap funds have a slope of 0.00171 (t = 3.57), nearly seven times the large-cap slope of 0.00025 (t = 0.85). The difference associated with fund size is similarly large. The difference associated with fees is somewhat smaller yet still statistically significant. In contrast, growth and value funds do not exhibit a significant difference in turnover-performance slopes.

Our model helps explain the differences across funds' turnover-performance slopes. Consider Panel A of Table II, which shows a larger slope for small-cap funds than for large-cap funds. From equation (13), the turnover-performance slope is increasing in the trading cost per unit of turnover, c, and decreasing in the autocorrelation of turnover, ρ. If a fund has higher trading costs (higher c), then it optimally adjusts its turnover less when profit opportunities π_t change (equation (5)). Therefore, any observed change in turnover must be associated with a larger change in profit opportunities and hence performance. Small-cap stocks are generally understood to be less liquid than large-cap stocks, so c is likely to be greater for small-cap funds. If a fund's turnover is less persistent (lower ρ), then the profits from last period's high turnover are less likely to be offset by trading costs from high turnover this period. Table III shows that the turnover of small-cap funds is less autocorrelated than that of large-cap funds. According to our model, having both a higher c and a lower ρ makes small-cap funds more likely to have a higher turnover-performance slope. We see from Table II that small-cap funds indeed have a higher estimated slope.

******************* INSERT TABLE III HERE *******************

A similar interpretation applies to the results in Panel C of Table II, which reports a significantly larger turnover-performance slope for small funds than for large funds. Small funds, by virtue of their trading smaller dollar amounts, are better suited for trading less-liquid stocks than are large funds. As stock size is surely an imperfect liquidity measure, it seems reasonable that fund size also helps proxy for the liquidity of the fund's holdings. That is, the c for small funds is likely to be greater than for large funds, even controlling for stock size. In addition, we see from Table III that small-fund turnover has a significantly lower autocorrelation than does large-fund turnover. Therefore, as with small-cap funds, having a higher c and a lower ρ makes small funds more likely to have a higher turnover-performance slope, also consistent with our estimates.

According to Panel B of Table II, there is no significant difference in turnover-performance slopes for value versus growth funds. Even this result is somewhat in keeping with our model, in that Edelen, Evans, and Kadlec (2013) report fairly similar trading costs (per unit of turnover) for value and growth funds, consistent with c being similar for both categories. On the other hand, we do see in Table III that turnover for growth funds has a higher autocorrelation than does turnover of value funds.

The differences in turnover-performance slopes related to expense ratio, reported in Panel D of Table II, can also be interpreted through our model. Recall from Section I.E that the turnover-performance relation should be stronger for more skilled funds. Expense ratio is closely related to the management fee rate, which may proxy for skill. One would expect managers with more skill to receive more fee revenue (e.g., Berk and Green (2004)), and fee revenue is proportional to the fee rate, conditional on a given fund size. The fee rate is not necessarily positively correlated with skill unconditionally, as that correlation depends on how size covaries with fees and skill in the cross-section, but it seems reasonable for managers with greater skill to charge higher fee rates.[18] Also, we find a higher slope for high-fee funds regardless of whether we condition on fund size by including controls in Panel D. Because a less-skilled (and thus lower-fee) fund trades suboptimally, some of the time variation in its turnover is unrelated to variation in true profit opportunities, producing a weaker turnover-performance relation.

Besides fees, we consider two additional proxies for fund skill. First, we take a fund's gross alpha over the fund's lifetime. Second, we compute gross alpha adjusted for both fund-level and industry-level returns to scale, following Pástor, Stambaugh, and Taylor (2015). For both proxies, we find that high-skill funds exhibit an even stronger turnover-performance relation compared to low-skill funds. These results, which are consistent with those in Table II based on fees, are in the online appendix.

[18]Consistent with this idea, Kacperczyk, van Nieuwerburgh, and Veldkamp (2014) report that funds with superior stock-picking skill charge significantly higher expense ratios.

The appendix also shows the results from an exercise that takes a different perspective on skill. Del Guercio and Reuter (2014) argue that broker-sold mutual funds face a weaker incentive to generate alpha than funds sold directly to retail investors. Motivated by their evidence, we compare the strength of the turnover-performance relation across these market segments.[19] We find that the relation is somewhat stronger in direct-sold funds than in broker-sold funds. The turnover-performance slope is 48% larger in magnitude for direct-sold funds, but the slope difference is only marginally significant (the p-value is 9%). This evidence points in the direction of direct-sold funds having a stronger incentive to perform, consistent with Del Guercio and Reuter (2014).

Finally, the average gross fund returns reported in Table III are also consistent with the model, in two ways. In each of the four panels of Table III, the average gross return of the top category is significantly greater than the bottom category, and the same is true for average turnover. The observed return-turnover link is consistent with the model's prediction of a positive cross-sectional turnover-performance relation (cf. equations (14) and (15)), and also with the positive cross-sectional slope in Table I.[20] In addition, for three of the four panels in Table II, the turnover-performance slope is significantly greater for the top category than for the bottom category. According to equation (13), the slope should be larger for funds with higher values of c and θ, holding ρ constant. According to equations (14) and (15), funds with higher c and θ should also have higher expected gross returns, holding average turnover constant. Therefore, the observed positive relation between the turnover-performance slope and the average gross return also jibes well with the model.

IV. Common Variation in Fund Turnover

Given our focus on the time variation in fund turnover, it seems natural to examine the extent to which this variation is common across funds. In this section, we aggregate turnover across funds and explore its time variation. In Section IV.A, we analyze comovement in fund turnover. In Section IV.B, we investigate the determinants of average fund turnover, which captures the common component of turnover. In Section IV.C, we study the predictive power of average turnover, constructed in various ways, for fund performance.

A. Comovement in Turnover

[19]To classify fund share classes by distribution channel, we use the approximation method of Sun (2014). We treat a share class as broker-sold if it has a non-zero front load, non-zero back load, or 12b-1 fee exceeding 25 bps; otherwise, we treat it as direct-sold. Following Del Guercio and Reuter (2014), we classify a fund as broker-sold (direct-sold) if at least 75% of its assets are broker-sold (direct-sold) on average over time.

[20]This evidence is also consistent with the result of Kacperczyk, van Nieuwerburgh, and Veldkamp (2014) that funds with superior stock-picking skill have significantly higher average turnover.

In our model, time variation in fund turnover is driven by variation in the fund's profit opportunities. Those opportunities are likely to be positively correlated across funds. Any mispriced stock presents a profit opportunity to many different funds that can potentially trade this stock. Moreover, if mispricing has market-wide causes such as liquidity disruptions or investor sentiment, many stocks can be mispriced at the same time. If profit opportunities are indeed correlated across funds, the model predicts comovement in fund turnover.

To see whether such comovement exists, we first compute category-level averages of individual fund turnover. We consider the same fund categories as before: three stock-size categories, three value-growth categories, three fund-size categories, and three expense-ratio categories. For each category, we compute the average turnover across all funds in that category. Specifically, average turnover in month t is the equal-weighted average turnover across category funds in the 12-month fiscal period that includes month t.

******************* INSERT FIGURE 1 HERE *******************

Figure 1 plots the time series of the category-level average turnover from 1979 to 2011. The figure shows strong comovement in turnover. The times series of average turnover are highly correlated both within and across the four panels. For example, the correlation between the average turnovers of small-cap and large-cap funds, both of which are plotted in Panel A, is 67%. We also observe high correlations between the average turnovers of value and growth funds (Panel B), small and large funds (Panel C), and high-fee and low-fee funds (Panel D). All pairwise correlations within each panel are reported in Table IV. In the context of our model, this evidence of comovement in turnover indicates that profit opportunities are positively correlated across funds—even across funds with different characteristics.

******************* INSERT TABLE IV HERE *******************

Panel B of Figure 1 provides more evidence on the result from Table III that growth funds trade more than value funds. Interestingly, the turnover of growth funds exceeds that of value funds not only on average but also in every single year, and by a wide margin. Value funds appear to be more patient than growth funds in exploiting their profit opportunities. We also see in Panel D that more expensive funds tend to turn over more than cheaper funds. The patterns in Panels A and C are less consistent over time.

In addition to computing average turnover at the category level, we compute it at the aggregate level. We let $AvgTurn$ denote the average of individual fund turnover computed across all funds. Analogous to the category-level variable, $AvgTurn_t$ is the average turnover across funds' 12-month fiscal periods that contain month t. $AvgTurn_t$, plotted in Panel A of Figure 2, fluctuates between 59% and 102% per year from 1979 to 2011.[21] It has a 95% correlation with the first principal component of individual fund turnover. Therefore, we view $AvgTurn_t$ as the simplest measure of the common component of turnover.

******************* INSERT FIGURE 2 HERE *******************

To shed more light on commonality in turnover, we regress individual fund turnover in month t on its common component, $AvgTurn_t$.[22] To isolate time-series variation in turnover, we run a panel regression with fund fixed effects. We report the results in the first column of Table V. The slope coefficient from the regression of $FundTurn$ on $AvgTurn$ is 0.65 ($t = 8.65$), indicating strong evidence of commonality in turnover.

******************* INSERT TABLE V HERE *******************

The evidence of commonality becomes even stronger when we replace $AvgTurn$ by category-level average turnover in the above regression. For each fund i, we calculate $AvgTurn\_Stock\_Size$ as the average turnover across funds in the same stock-size category as fund i. In the regression of $FundTurn$ on $AvgTurn\_Stock\_Size$, the category-level average is highly significant ($t = 8.94$), and the R^2 exceeds that from the regression of $FundTurn$ on $AvgTurn$. We also calculate average turnover across funds in the same value-growth category ($AvgTurn\_Stock\_VG$), same fund-size category ($AvgTurn\_Fund\_Size$), and same expense-ratio category ($AvgTurn\_Fund\_Exp$). All of these category-level averages are significantly correlated with $FundTurn$ in simple regressions, and all except for $AvgTurn\_Stock\_VG$ produce higher within-fund R^2's than $AvgTurn$ (see columns 2 through 5 of Table V). In a multiple regression of $FundTurn$ on all four category-level averages, three of the averages obtain significant slopes; only $AvgTurn\_Stock\_VG$ is insignificant (see column 6). Finally, we calculate average turnover across "similar" funds, $AvgTurnSim$, by averaging across funds in the same stock-size, fund-size, and expense-ratio categories. (We exclude value-growth due to its insignificance in column 6.) In a univariate regression, this variable produces a higher within-fund R^2 than any of the category-level averages. In a multiple regression of $FundTurn$ on $AvgTurn$ and $AvgTurnSim$, both averages come in significantly, and the

[21]CRSP turnover data are missing in 1991 for unknown reasons. We therefore treat $AvgTurn$ as missing in 1991 in our regressions. In Figure 2, though, we fill in average turnover in 1991 by using Morningstar data, for aesthetic purposes. We rely on CRSP turnover data in our analysis because Morningstar is ambiguous about the timing of funds' fiscal years.

[22]For the purpose of this regression, we recalculate $AvgTurn_t$ corresponding to each fund i as the average turnover across all funds $j \neq i$. By excluding fund i from the calculation of average turnover, we exclude any mechanical correlation that could create a spurious perception of commonality. Analogously, we exclude fund i from all other measures of average turnover discussed in the following paragraph.

t-statistic on $AvgTurnSim$ is higher (7.66 vs. 5.71; see column 8). This evidence shows that commonality in turnover is especially strong among funds with similar characteristics.

B. Mispricing and Trading

When do funds trade more than usual? In our model, funds trade more when their profit opportunities are better. If such opportunities arise from mispricing, then funds should trade more in periods with more mispricing. We thus ask whether fund turnover is higher when mispricing is more likely. We use three proxies for the likelihood of mispricing: $Sentiment_t$, $Volatility_t$, and $Liquidity_t$. We plot the three series in Panel B of Figure 2.

The first mispricing proxy, $Sentiment_t$, is the value in month t of Baker and Wurgler's (2006, 2007) investor-sentiment index. If sentiment-driven investors participate more heavily in the stock market during high-sentiment periods, the mispricing such investors create is more likely to occur during those periods (e.g., Stambaugh, Yu, and Yuan, 2012). We thus expect funds exploiting such mispricing to trade more when sentiment is high. Indeed, time-series regressions of both $FundTurn_{i,t}$ and $AvgTurn_t$ on $Sentiment_t$ produce significantly positive slopes ($t = 3.27$ and $t = 3.17$, respectively), as shown in columns 1 and 5 of Table VI. We include a time trend in both regressions, given the positive trend in $AvgTurn_t$ evident in Figure 2. The time trend is significant in the latter regression but not in the former. The R^2 in the regression of $AvgTurn_t$ on $Sentiment_t$ and the time trend exceeds the R^2 from the regression on the time trend alone by 0.171. Sentiment, in other words, explains a substantial fraction of the time variation in aggregate fund turnover.

******************* INSERT TABLE VI HERE *******************

The second mispricing proxy, $Volatility_t$, is the cross-sectional standard deviation in month t of the returns on individual U.S. stocks.[23] The rationale for this variable is that higher volatility corresponds to greater uncertainty about future values and thus greater potential for investors to err in assessing those values. As a result, periods of high volatility admit greater potential mispricing, and we expect funds exploiting such mispricing to trade more when volatility is high. Consistent with this prediction, regressions of both $FundTurn_{i,t}$ and $AvgTurn_t$ on $Volatility_t$ produce significantly positive slopes ($t = 7.69$ and $t = 7.23$, respectively), as shown in columns 2 and 6 of Table VI. The R^2 in the latter regression, which again includes a time trend, exceeds the R^2 in the trend-only regression by 0.188.

The third proxy, $Liquidity_t$, is the value in month t of the stock-market liquidity measure of Pástor and Stambaugh (2003). Empirical evidence suggests that higher liquidity is accom-

[23]We thank Bryan Kelly for providing this series.

panied by greater market efficiency (e.g., Chordia, Roll, and Subrahmanyam, 2008, 2011). In other words, periods of lower liquidity are more susceptible to mispricing. Therefore, we might expect funds to trade more when liquidity is lower. On the other hand, lower liquidity also implies higher transaction costs, which could discourage funds from trading. Our evidence suggests that the former effect is stronger: Regressing $FundTurn_{i,t}$ and $AvgTurn_t$ on $Liquidity_t$ yields significantly negative slope estimates ($t = -4.53$ and $t = -4.14$, respectively), reported in columns 3 and 7 of Table VI. Including $Liquidity_t$ increases the R^2 versus the trend-only regression by a more modest amount than the other two proxies.

When all three mispricing proxies are included simultaneously as regressors, each enters with a coefficient and t-statistic similar to when included just by itself. These all-inclusive regressions, reported in columns 4 and 8 of Table VI, also add two additional variables that control for potential effects of the business cycle and recent stock-market returns, but neither variable enters significantly. (The two variables are the Chicago Fed National Activity Index and the return on the CRSP value-weighted market index over the previous 12 months.) The combined ability of the three mispricing proxies to explain variance in $AvgTurn_t$ is substantial: the R^2 exceeds that of the trend-only regression by 0.324.[24] Overall, the results make sense: funds trade more when there is more mispricing.

What mispricing are funds exploiting? To see whether funds trade based on well-known market anomalies, we regress the returns of eleven such anomalies, as well as their composite return, on lagged average fund turnover. The eleven anomalies, whose returns we obtain from Stambaugh, Yu, and Yuan (2012), involve sorting stocks based on two measures of financial distress, two measures of stock issuance, accruals, net operating assets, momentum, gross profitability, asset growth, return on assets, and the investment-to-assets ratio. We find no significant slopes on average turnover. To the extent that funds trade more when there is more mispricing, they are exploiting mispricing beyond these eleven anomalies.

Finally, we consider the role of stock market turnover in explaining $AvgTurn_t$. We measure market turnover as total dollar volume over the previous 12 months divided by total market capitalization of ordinary common shares in CRSP. Market turnover reflects trading by all entities, including mutual funds, so it could potentially be related to $AvgTurn_t$. It could also be related to $Sentiment_t$, which is constructed as the first principal component

[24]If we exclude the time trend from the regressions, we find results similar to those reported in Table VI. $Volatility$ and $Liquidity$ continue to enter significantly with the same signs as in Table VI, and the business cycle and market return remain insignificant. The only difference relates to $Sentiment$, whose coefficient retains the positive sign but loses statistical significance in the regression that involves $AvgTurn$ (it remains significant in the regression that involves $FundTurn$). This evidence suggests that $Sentiment$ is better at capturing deviations of $AvgTurn$ from its trend than in capturing the raw variation in $AvgTurn$.

of six variables that include NYSE turnover. However, when we add market turnover to the all-inclusive specification in column 8 of Table VI, it does not enter significantly, whereas the slope on $Sentiment_t$ remains positive and significant. The other two mispricing proxies also retain their signs and significance, and the remaining variables remain insignificant. In short, adding market turnover does not affect our inferences in Table VI.

C. Predicting Fund Performance

Given its significant link to the mispricing proxies, it is natural to ask whether the common component of fund turnover helps predict fund performance. In fact, a positive relation between the common component and future fund performance can be motivated directly within our model, in two different ways.

First, we assume that funds trade optimally but their turnover is observed with error. In the model, optimal fund turnover, X_t^* from equation (5), results solely from the fund's decision to change the composition of its portfolio. In the data, however, inflows and outflows of investors' capital also give rise to trading by the fund. The reported turnover measure that we observe empirically, $\tilde{X}_t$, abstracts from flow effects, but only imperfectly, so it is not precisely equal to X_t^*. In other words, we observe

$$\tilde{X}_t = X_t^* + u_t \ , \tag{29}$$

where u_t denotes the measurement error. We assume that u_t has mean zero and is uncorrelated with X_t^*. With many funds in the market, an additional explanatory variable useful in addressing this error-in-variable problem is the cross-sectional average turnover, which we denote by $\overline{X}_t$. Intuitively, since turnover comoves across funds, average turnover contains additional information about a fund's true turnover beyond the information in our imperfect $FundTurn$ measure. We assume that there are sufficiently many funds that the measurement errors in turnover diversify away when computing $\overline{X}_t$. Let

$$X_t^* = \beta_X \overline{X}_t + \phi_t \ , \tag{30}$$

and assume that ϕ_t is uncorrelated with $\overline{X}_t$ and that the residuals ϕ_t, u_t, and ϵ_{t+1} are mutually uncorrelated. Let σ_u^2 and σ_ϕ^2 denote the variances of u_t and ϕ_t, respectively. Consider the linear regression of the fund's return R_{t+1} on fund turnover $\tilde{X}_t$ and average turnover $\overline{X}_t$:

$$R_{t+1} = \hat{\theta}_0 + \hat{\theta}_1 \tilde{X}_t + \hat{\theta}_2 \overline{X}_t + e_{t+1} \ . \tag{31}$$

As we show in the Appendix, the slope coefficients have probability limits

$$\theta_1 \quad = \quad \left(\frac{\sigma_\phi^2}{\sigma_\phi^2 + \sigma_u^2} \right) b \tag{32}$$

$$\theta_2 = \left(\frac{\beta_X \sigma_u^2}{\sigma_\phi^2 + \sigma_u^2} \right) b \; . \tag{33}$$

Both θ_1 and θ_2 are positive as long as b from equation (11) and β_X from equation (30) are positive, which is consistent with the data (see Tables I and V). Moreover, the coefficient on average turnover (θ_2) is large when the measurement error in turnover is large (i.e., σ_u^2 large) and when the commonality in turnover is large (i.e., σ_ϕ^2 small). Given our strong evidence of commonality, our model suggests a role for average turnover in predicting fund performance. Since the commonality is especially strong among funds with similar characteristics, average turnover of similar funds could be particularly useful in predicting performance.

Another way to motivate the role for average turnover, again hinging on commonality in turnover, relies on the model's extension with suboptimal trading (Section I.E). Suppose that funds trade suboptimally, so that only a fraction of their turnover involves exploiting true profit opportunities. Also suppose that funds' profit opportunities are positively correlated over time (i.e., there is common variation in funds' π_t's), as they are when the degree of mispricing varies over time in a way that many funds can exploit. Given the commonality in π_t, equation (5) implies common variation in funds' X_t^*'s. Any given fund's observed turnover X_t is a noisy proxy for its optimal unobserved turnover X_t^*, but averaging X_t across many funds gives a less-noisy proxy for the average X_t^*. Given the common variation in X_t^*, that proxy for the average X_t^* provides information about any given fund's X_t^* in addition to the information provided by the fund's own X_t. As shown in the Appendix, a fund's performance depends on both its X_t and its X_t^*, so not only its own X_t but also the average X_t predicts the fund's performance. Intuitively, a fund trades more—and the fund's subsequent performance is better—when the fund identifies more profit opportunities. When many funds identify such opportunities, average turnover is higher, and there is more mispricing in general. That is, heavier trading by other funds indicates more mispricing. Even when a fund's own manager does not identify unusually many opportunities in a given period, the opportunities he does identify are likely to be more profitable if there is generally more mispricing in that period. In this way, suboptimal trading also creates a role for the turnover of other funds, especially similar funds, in predicting fund performance.

We find such a role in the data. We run a panel regression of the gross benchmark-adjusted fund return ($R_{i,t}$) on average lagged turnover, with fund fixed effects. We consider two measures of average turnover: $AvgTurnSim$, averaging across similar funds, and $AvgTurn$, averaging across all funds. Specifically, we calculate $AvgTurnSim_{i,t-1}$ by averaging $FundTurn_{j,t-1}$ across funds $j \neq i$ in the same stock-size, fund-size, and expense-ratio category as fund i. We calculate $AvgTurn_{i,t-1}$ by averaging $FundTurn_{j,t-1}$ across all funds $j \neq i$.[25] Column 1 of Table VII shows that the slope from the regression of $R_{i,t}$ on $AvgTurnSim_{i,t-1}$ is positive and significant ($t = 3.29$), indicating that the common component of similar funds' trading helps predict individual fund performance. The magnitude of the estimate, 0.0021, implies substantial economic significance. Given the average time-series standard deviation of $AvgTurnSim_{i,t-1}$, 0.172, a one-standard-deviation increase in the variable translates to an increase in expected return of 0.43% per year ($= 0.0021 \times 0.172 \times 1200$).[26]

******************** INSERT TABLE VII HERE ********************

Since we find more commonality among similar funds, we expect $AvgTurnSim$ to predict performance better than $AvgTurn$ does. This is indeed what we find: column 2 of Table VII shows a positive but statistically insignificant relation between $R_{i,t}$ and $AvgTurn_{i,t-1}$.

The information in $AvgTurnSim$ about a fund's subsequent performance is undiminished by conditioning on the fund's own turnover. Column 4 of Table VII shows that the slope and t-statistic for $AvgTurnSim$ are little changed by controlling for $FundTurn$. Similarly, the significance of the slope on $FundTurn$ is little changed by controlling for $AvgTurnSim$. The fund's performance is predictable by both similar funds' average turnover and the fund's own turnover. In the context of our model, we find $\hat{\theta}_1 > 0$ and $\hat{\theta}_2 > 0$ in equation (31).

Finally, when all three turnover measures are included on the right-hand side of the regression, both $AvgTurnSim$ and $FundTurn$ enter significantly whereas the slope on $AvgTurn$ is positive but insignificant. Again, we see that averaging turnover across similar funds, which exhibit stronger commonality in turnover compared to dissimilar funds, improves the predictive power. In short, Table VII shows that a fund's performance is predictable not only by the fund's own turnover but also by the average turnover of similar funds.

V. Conclusions

We develop a model of fund trading in the presence of time-varying profit opportunities. The model's key implication is a positive time-series relation between an active fund's

[25]Note that $AvgTurnSim_{i,t-1}$ and $AvgTurn_{i,t-1}$ use only information available before month t because they are averages of turnovers computed over 12-month periods that end before month t. It is thus reasonable to use $AvgTurnSim_{i,t-1}$ and $AvgTurn_{i,t-1}$ to predict performance in month t. Also note that the notation for time subscripts is complicated by the fact that funds report turnover only annually. In Section IV.A, we let $AvgTurn_t$ denote average turnover across funds' 12-month fiscal periods that contain month t. That notation is slightly inconsistent with the notation in this section because given our definition of $FundTurn_{i,t}$, the contemporaneous average turnover in Section IV.A is the average of $FundTurn_{i,t+11}$ across i. We prefer to use the notation $AvgTurn_t$ (instead of $AvgTurn_{t+11}$) in Section IV.A to emphasize the contemporaneous nature of the analysis in that section. We hope the reader will pardon this slight abuse of notation.

[26]The regressions in Table VII exclude a time trend, but the results are very similar if we include one.

turnover and its subsequent benchmark-adjusted return. We find strong support for this implication in a large sample of active equity mutual funds. Funds exhibit an ability to identify time-varying profit opportunities and adjust their trading activity accordingly. This time-series relation between turnover and performance is stronger than the cross-sectional relation, as our model predicts. The model also predicts a stronger time-series relation for funds trading less-liquid stocks. Indeed, we find a stronger relation for small-stock funds and small funds. We also find a stronger relation for funds that charge higher fees, consistent with such funds having greater skill in identifying time-varying profit opportunities.

We provide strong evidence of commonality in fund turnover. Turnover's common component, average turnover, is positively correlated with mispricing proxies. Funds trade more when investor sentiment is high, when cross-sectional stock volatility is high, and when stock market liquidity is low, consistent with funds identifying more profit opportunities in periods when mispricing is more likely. Commonality in turnover is especially high among funds sharing similar characteristics. Average turnover of similar funds positively predicts fund returns, even controlling for the fund's own turnover. This predictive ability of average turnover is consistent with an individual fund's observed turnover being a noisy proxy for the fund's true turnover. Average turnover of similar funds helps capture a fund's true turnover and thereby helps predict the fund's performance. Average turnover's predictive ability is also consistent with suboptimal trading by funds, where only some trades exploit true profit opportunities. Whatever opportunities a fund does identify are likely to be more profitable when mispricing is more prevalent, as indicated by similar funds trading more heavily.

Heavier trading by funds when mispricing is more likely underscores the role of active management in the price discovery process. While the active management industry may not provide superior net returns to its investors (consistent with both theory and evidence), it creates a valuable externality. The combined trading of many funds helps correct prices and thereby enables more efficient capital allocation. French (2008) characterizes his estimated cost of active management as a societal cost of price discovery. Stambaugh's (2014) calibration of a general equilibrium model implies that active management corrects a large portion of the mispricing that would otherwise exist in the presence of noise traders. Our results support this view of active management's societal value, given our evidence that funds have skill and that they more actively apply that skill when mispricing is more likely.

Appendix A. Model Extension: Suboptimal Trading

Here we extend our basic model to incorporate suboptimal trading by funds. When a fund trades suboptimally, its trading in period t achieves less than the maximized value of expected profit in equation (3). Its turnover X_t need not equal X_t^*, and its trades may be less profitable than if they were chosen optimally, so that equation (1) no longer characterizes the relation between turnover and before-cost profit. We assume the fund's expected after-cost profit arising from its turnover X_t is equal to

$$Y_t = \delta[P(X_t^*) - C(X_t^*)] \ , \tag{A1}$$

with $\delta \leq 1$. Optimal trading corresponds to $\delta = 1$. We also assume that

$$\mathrm{E}(X_t^*|X_t, \delta) = X_t \tag{A2}$$

and

$$\mathrm{E}(\delta|X_t) = \mathrm{E}(\delta) \equiv \bar{\delta} \ . \tag{A3}$$

We also assume that the autoregressive process in equation (9) applies to X_t.

The fund's before-fee realized return in period $t+1$, R_{t+1}, is given by realized after-cost profit arising from turnover in period t—expected profit Y_t plus a random deviation η_{t+1}—plus the difference between trading costs in periods t and $t+1$:

$$R_{t+1} = Y_t + C(X_t) - C(X_{t+1}) + \eta_{t+1} \ . \tag{A4}$$

The difference in trading costs arises because the cost of the trading included in computing expected profit, Y_t, is incurred in period t and thus does not enter R_{t+1}. That return instead includes the cost of trading in period $t+1$. Combining (2), (7), and (A1) with (A4) gives

$$R_{t+1} = \delta \left[\frac{c(1+\gamma)}{1-\theta} (X_t^*)^{1+\gamma} - c(X_t^*)^{1+\gamma} \right] + c(X_t)^{1+\gamma} - c(X_{t+1})^{1+\gamma} + \eta_{t+1} \ . \tag{A5}$$

As discussed in Section IV, both X_t and (the unobserved) X_t^* contain information about R_{t+1}. To obtain the time-series relation containing just X_t, we again assume $\gamma \approx 0$ and then apply (9) and (A2) to obtain

$$\mathrm{E}(R_{t+1}|X_t, \delta) \quad = \quad \bar{a} + \tilde{b} X_t \ , \tag{A6}$$

where

$$\bar{a} \quad = \quad -c(1-\rho)\mathrm{E}(X_t) \tag{A7}$$

$$\tilde{b} \quad = \quad c \left[\frac{1-\theta(1-\delta)}{1-\theta} - \rho \right] \ . \tag{A8}$$

Note that $\tilde{b}$ is increasing in δ. The lower is this dimension of a fund's skill, the weaker is the fund's turnover-performance relation. In the optimal-trading case of $\delta = 1$, $\tilde{b} = b$ in (13).

The time-series relation in (A6) pertains to a given fund with a given δ, but the values of δ can differ across funds. Given (A3), taking the expectation of (A6) with respect to δ, applying the rule of iterated expectations, yields (17) through (19). Taking the unconditional expectation of (17), using (A7) and (19), then yields the cross-sectional turnover-performance relation given by (20) and (21).

Appendix B. The Pooled Fixed-Effects Slope Estimator for an Unbalanced Panel as a Weighted Average of Single-Equation Slope Estimators

Here we derive a result supporting the interpretations of the time-series and cross-sectional slopes in Table I as weighted averages of fund-by-fund and period-by-period regressions. The result also sheds light on the well-known estimator of Fama and MacBeth (1973). Consider the fixed-effects panel regression model

$$y_{ij} = a_i + bx_{ij} + e_{ij} \ , \tag{B1}$$

where i takes N different values in the data. Let m_i denote the number of observations whose first subscript is equal to i. For each i, define

y_i: $m_i \times 1$ vector of y_{ij} observations,

x_i: $m_i \times 1$ vector of x_{ij} observations,

ι_i: $m_i \times 1$ vector of ones.

Also define the sample variance of the elements of x_i,

$$\hat{\sigma}^2_{x_i} = \frac{x_i' x_i}{m_i} - \left(\frac{\iota_i' x_i}{m_i} \right)^2 \ , \tag{B2}$$

and the single-equation least-squares estimator,

$$\begin{bmatrix} \hat{a}_i \\ \hat{b}_i \end{bmatrix} = (X_i' X_i)^{-1} X_i' y_i, \quad \text{where } X_i = [\iota_i \ x_i] \ . \tag{B3}$$

Note that the slope coefficient $\hat{b}_i$ can be written as

$$\hat{b}_i = \frac{1}{\hat{\sigma}^2_{x_i}} \left(\frac{x_i' y_i}{m_i} - \bar{x}_i \bar{y}_i \right) \ , \tag{B4}$$

where $\bar{x}_i$ and $\bar{y}_i$ are the sample means of x_i and y_i, respectively (i.e., $\bar{x}_i = \iota_i' x_i / m_i$ and $\bar{y}_i = \iota_i' y_i / m_i$). For the pooled sample, define

$$X = \begin{bmatrix} \iota_1 & 0 & \cdots & 0 & x_1 \\ 0 & \iota_2 & & \vdots & x_2 \\ \vdots & & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & \iota_N & x_N \end{bmatrix}, \quad y = \begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix}, \quad x = \begin{bmatrix} x_1 \\ \vdots \\ x_N \end{bmatrix}, \tag{B5}$$

and the least-squares estimator

$$\begin{bmatrix} \hat{a}_1 \\ \vdots \\ \hat{a}_N \\ \hat{b} \end{bmatrix} = (X'X)^{-1} X'y \ . \tag{B6}$$

PROPOSITION A1. *The fixed-effects slope estimator $\hat{b}$ obeys the relation*

$$\hat{b} = \sum_{i=1}^{N} w_i \hat{b}_i \ , \tag{B7}$$

where

$$w_i = \frac{m_i \hat{\sigma}_{x_i}^2}{\sum_{k=1}^{N} m_k \hat{\sigma}_{x_k}^2} \ . \tag{B8}$$

Proof. First observe

$$\begin{aligned} X'X &= \begin{bmatrix} \iota_1' & 0 & \cdots & 0 \\ 0 & \iota_2' & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & & & \iota_N' \\ x_1' & x_2' & \cdots & x_N' \end{bmatrix} \begin{bmatrix} \iota_1 & 0 & \cdots & 0 & x_1 \\ 0 & \iota_2 & & \vdots & x_2 \\ \vdots & & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & \iota_N & x_N \end{bmatrix} \\ &= \begin{bmatrix} m_1 & 0 & \cdots & 0 & \iota_1' x_1 \\ 0 & m_2 & & \vdots & \iota_2' x_2 \\ \vdots & & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & m_N & \iota_N' x_N \\ \iota_1' x_1 & \iota_2' x_2 & \cdots & \iota_N' x_N & x'x \end{bmatrix} \\ &= \begin{bmatrix} D & v \\ v' & q \end{bmatrix}, \end{aligned} \tag{B9}$$

and therefore

$$(X'X)^{-1} = \begin{bmatrix} D^{-1} + D^{-1}v(q - v'D^{-1}v)^{-1}v'D^{-1} & -D^{-1}v(q - v'D^{-1}v)^{-1} \\ -(q - v'D^{-1}v)^{-1}v'D^{-1} & (q - v'D^{-1}v)^{-1} \end{bmatrix} . \tag{B10}$$

Next observe that the ith element of the vector $D^{-1}v$ contains the sample mean of the elements of x_i,

$$D^{-1}v = \begin{bmatrix} (\iota_1' x_1)/m_1 \\ \vdots \\ (\iota_N' x_N)/m_N \end{bmatrix} = \begin{bmatrix} \bar{x}_1 \\ \vdots \\ \bar{x}_N \end{bmatrix} = \bar{x} \ , \tag{B11}$$

and that

$$\begin{aligned} q - v' D^{-1} v &= x'x - \bar{x}' D \bar{x} \\ &= x_1' x_1 + \cdots + x_N' x_N - m_1 \bar{x}_1^2 - \cdots - m_N \bar{x}_N^2 \\ &= m_1 \left(\frac{x_1' x_1}{m_1} - \bar{x}_1^2 \right) + \cdots + m_N \left(\frac{x_N' x_N}{m_N} - \bar{x}_N^2 \right) \\ &= m_1 \hat{\sigma}_{x_1}^2 + \cdots + m_N \hat{\sigma}_{x_N}^2 \ . \end{aligned} \tag{B12}$$

Also,

$$X'y = \begin{bmatrix} \iota_1' & 0 & \cdots & 0 \\ 0 & \iota_2' & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & & & \iota_N' \\ x_1' & x_2' & \cdots & x_N' \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} \iota_1' y_1 \\ \iota_2' y_2 \\ \vdots \\ \iota_N' y_N \\ x'y \end{bmatrix} \ . \tag{B13}$$

The last element of the pooled least-squares estimator in (B6) can now be computed by pre-multiplying the vector in (B13) by the last row of the matrix in (B10), using (B11) and (B12) and then (B4), to obtain

$$\begin{aligned} \hat{b} &= \left(m_1 \hat{\sigma}_{x_1}^2 + \cdots + m_N \hat{\sigma}_{x_N}^2 \right)^{-1} \left(-\bar{x}_1 \iota_1' y_1 - \cdots - \bar{x}_N \iota_N' y_N + x_1' y_1 + \cdots + x_N' y_N \right) \\ &= \left(m_1 \hat{\sigma}_{x_1}^2 + \cdots + m_N \hat{\sigma}_{x_N}^2 \right)^{-1} \left[(x_1' y_1 - m_1 \bar{x}_1 \bar{y}_1) + \cdots + (x_N' y_N - m_N \bar{x}_N \bar{y}_N) \right] \\ &= \left(m_1 \hat{\sigma}_{x_1}^2 + \cdots + m_N \hat{\sigma}_{x_N}^2 \right)^{-1} \left[m_1 \left(\frac{x_1' y_1}{m_1} - \bar{x}_1 \bar{y}_1 \right) + \cdots + m_N \left(\frac{x_N' y_N}{m_N} - \bar{x}_N \bar{y}_N \right) \right] \\ &= \left(m_1 \hat{\sigma}_{x_1}^2 + \cdots + m_N \hat{\sigma}_{x_N}^2 \right)^{-1} \left[m_1 \hat{\sigma}_{x_1}^2 \hat{b}_1 + \cdots + m_N \hat{\sigma}_{x_N}^2 \hat{b}_N \right] \\ &= \sum_{i=1}^{N} w_i \hat{b}_i \ . \end{aligned} \tag{B14}$$

Q.E.D.

We can now interpret the time-series coefficient in the upper-left cell of Table I. Let $\widehat{b}_i$ denote the estimated slope from the time-series regression in equation (23). Then $\widehat{b}$ from equation (26) is given by

$$\widehat{b} = \sum_{i=1}^{N} w_i \widehat{b}_i \ , \tag{B15}$$

where the weights w_i are given by

$$w_i = \frac{T_i \widehat{\sigma}_{x_i}^2}{\sum_{n=1}^{N} T_n \widehat{\sigma}_{x_n}^2} \ , \tag{B16}$$

T_i is the number of observations for fund i, and $\widehat{\sigma}^2_{x_i}$ is the sample variance of $X_{i,t-1}$ across t.

Similarly, we can interpret the cross-sectional coefficient in the bottom-right cell of Table I. Let $\widehat{b}_t$ denote the slope from the cross-sectional regression of $R_{i,t}$ on $X_{i,t-1}$ estimated at time t. Then $\widehat{b}$ from equation (28) obeys the relation

$$\widehat{b} = \sum_{t=1}^{T} w_t \widehat{b}_t \ , \tag{B17}$$

where the weights w_t are given by

$$w_t = \frac{N_t \widehat{\sigma}^2_{x_t}}{\sum_{s=1}^{T} N_s \widehat{\sigma}^2_{x_s}} \ , \tag{B18}$$

N_t is the number of observations at time t, and $\widehat{\sigma}^2_{x_t}$ is the sample variance of $X_{i,t-1}$ across i. The relation in equation (B17) is very general and therefore of independent interest. It provides an explicit link between panel regressions with time fixed effects and pure cross-sectional regressions. It also sheds light on the well-known estimator of Fama and MacBeth (1973), which is an equal-weighted average of $\widehat{b}_t$. The Fama-MacBeth estimator is a special case of equation (B17) if the panel is balanced (i.e., $N_t = N$ for all t) and the cross-sectional variance of $X_{i,t-1}$ is time-invariant (i.e., $\widehat{\sigma}^2_{x_t} = \widehat{\sigma}^2_x$ for all t).

Appendix C. Proof of Statements in Equations (32) and (33)

We now prove the statements related to equations (32) and (33) from Section IV.C. Combining equations (11) and (30) gives

$$R_{t+1} = a + b\beta_X \overline{X}_t + b\phi_t + \epsilon_{t+1} \ , \tag{C1}$$

and combining (29) and (30) gives

$$\tilde{X}_t = \beta_X \overline{X}_t + \phi_t + u_t \ . \tag{C2}$$

The probability limits of the estimated regression slope coefficients in (31) are given by

$$\begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} = \begin{bmatrix} \mathrm{Var}(\tilde{X}_t) & \mathrm{Cov}(\tilde{X}_t, \overline{X}_t) \\ \mathrm{Cov}(\tilde{X}_t, \overline{X}_t) & \mathrm{Var}(\overline{X}_t) \end{bmatrix}^{-1} \begin{bmatrix} \mathrm{Cov}(R_{t+1}, \tilde{X}_t) \\ \mathrm{Cov}(R_{t+1}, \overline{X}_t) \end{bmatrix} . \tag{C3}$$

Let $\sigma^2_{\bar{X}}$ denote the variance of $\overline{X}_t$. Equations (C1) and (C2), along with the assumptions that all quantities on the right-hand sides of those equations are mutually uncorrelated, allow

(C3) to be simplified as

$$\begin{aligned}
\left[\begin{array}{c} \theta_1 \\ \theta_2 \end{array}\right] &= \left[\begin{array}{cc} \beta_X^2\sigma_{\bar{X}}^2+\sigma_\phi^2+\sigma_u^2 & \beta_X\sigma_{\bar{X}}^2 \\ \beta_X\sigma_{\bar{X}}^2 & \sigma_{\bar{X}}^2 \end{array}\right]^{-1}\left[\begin{array}{c} b(\beta_X^2\sigma_{\bar{X}}^2+\sigma_\phi^2) \\ b\beta_X\sigma_{\bar{X}}^2 \end{array}\right] \\
&= \frac{1}{\sigma_{\bar{X}}^2(\sigma_\phi^2+\sigma_u^2)}\left[\begin{array}{cc} \sigma_{\bar{X}}^2 & -\beta_X\sigma_{\bar{X}}^2 \\ -\beta_X\sigma_{\bar{X}}^2 & \beta_X^2\sigma_{\bar{X}}^2+\sigma_\phi^2+\sigma_u^2 \end{array}\right]\left[\begin{array}{c} b(\beta_X^2\sigma_{\bar{X}}^2+\sigma_\phi^2) \\ b\beta_X\sigma_{\bar{X}}^2 \end{array}\right] \\
&= \left[\begin{array}{c} \left(\frac{\sigma_\phi^2}{\sigma_\phi^2+\sigma_u^2}\right)b \\ \beta_X\left(\frac{\sigma_u^2}{\sigma_\phi^2+\sigma_u^2}\right)b \end{array}\right]. \qquad \text{(C4)}
\end{aligned}$$

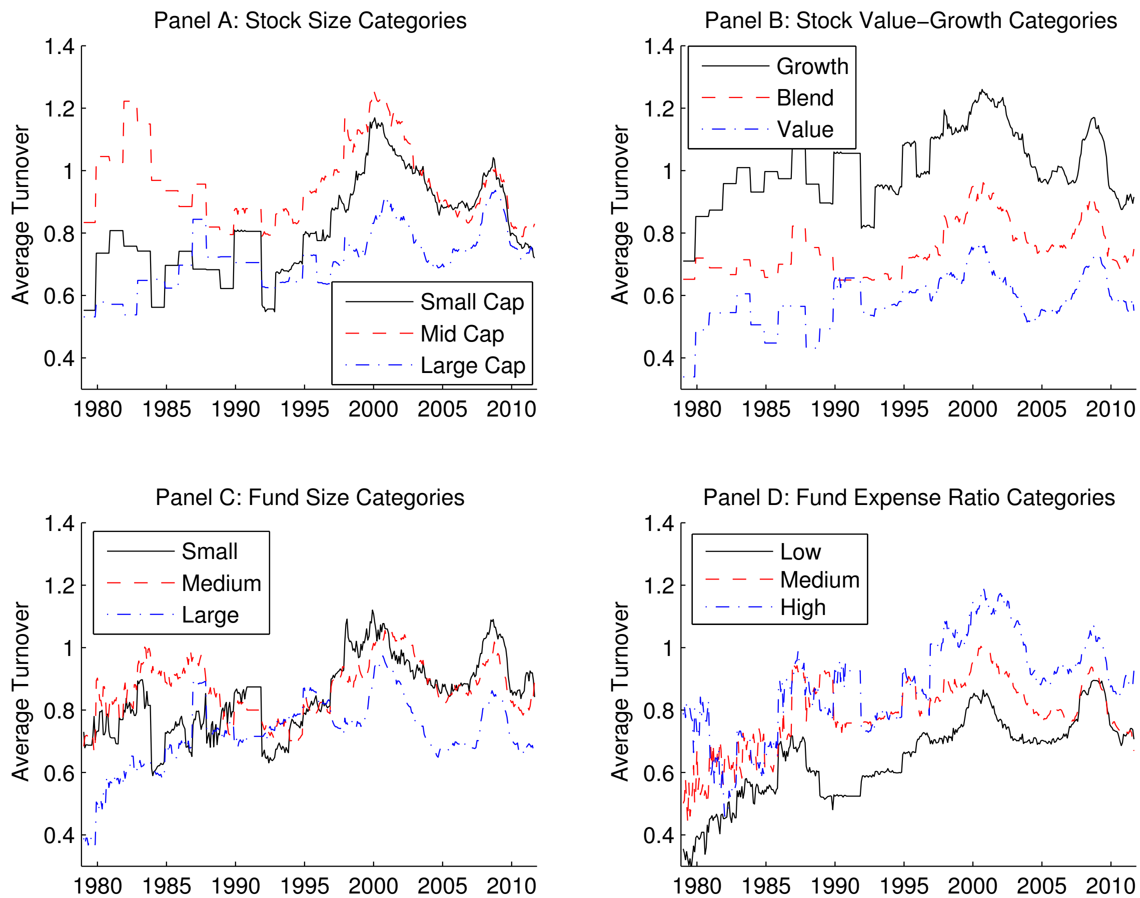

Figure 1. Average Turnover Across Fund Categories. Each panel splits funds into three categories and plots the time series of category-level average turnover. Average turnover in month t is the equal-weighted average turnover across category funds in the 12-month period that includes month t. Panel A compares small-cap, mid-cap, and large-cap funds; we use Morningstar's stock-size classification. Panel B compares growth, blend, and value funds; we use Morningstar's value-growth classification. Panel C categorizes funds according to their size, splitting the sample each month into terciles based on their lagged assets under management. Panel D categorizes funds according to their expense ratio, splitting the sample each month into terciles based on their lagged expense ratio. Data are from 1979–2011.

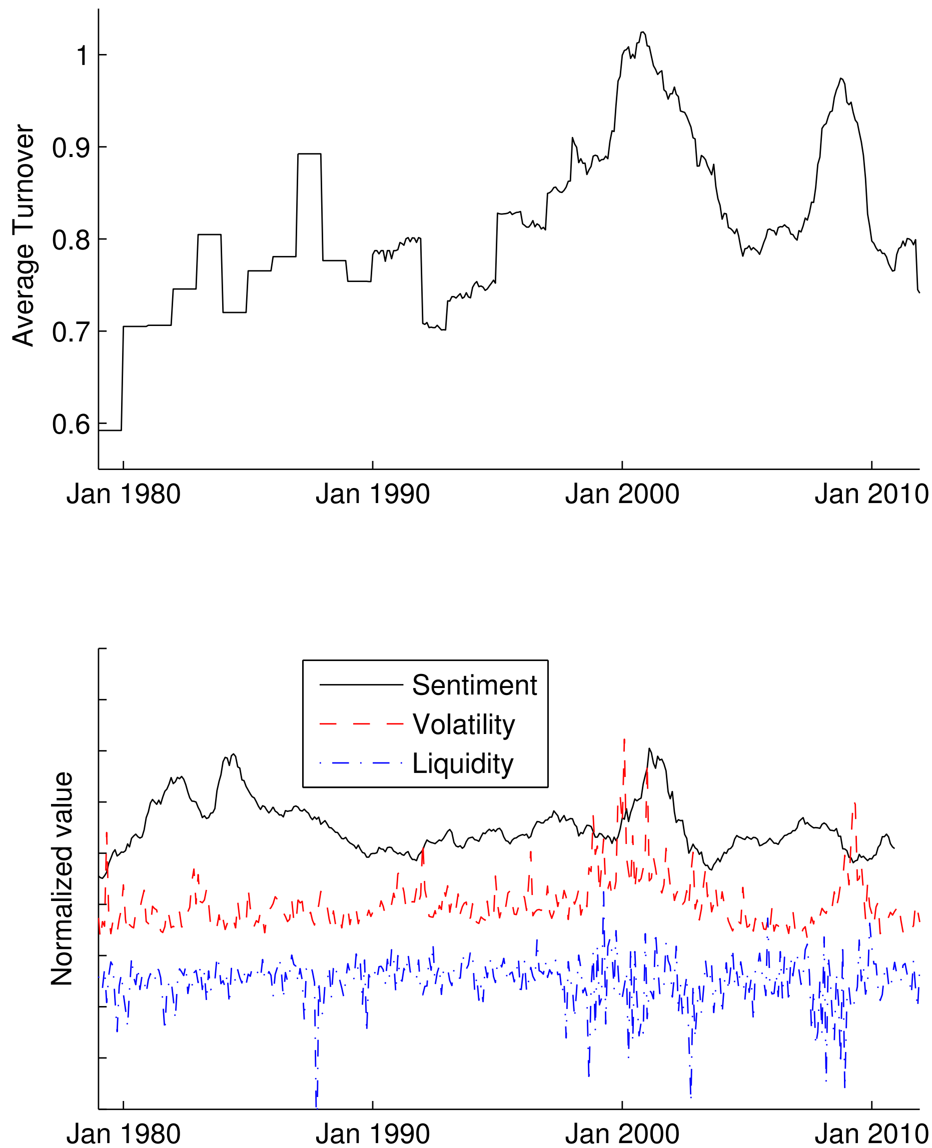

Figure 2. Average Turnover, Sentiment, Volatility, and Liquidity over time. Panel A plots the time series of $AvgTurn_t$, the equal-weighted average turnover across sample funds in the 12-month period that includes month t. Panel B plots the time series of *Sentiment* (from Baker and Wurgler, 2007); $Volatility$ (the cross-sectional standard deviation in monthly stock returns); and *Liquidity* (the level of aggregate liquidity from Pástor and Stambaugh, 2003).

Table I
Turnover-Performance Relation in the Cross Section and Time Series

The table reports the estimated slope coefficients from four different panel regressions of $R_{i,t}$ on $FundTurn_{i,t-1}$. $R_{i,t}$ is fund i's net return plus expense ratio minus Morningstar's designated benchmark return in month t. $FundTurn_{i,t-1}$ is fund i's turnover for the most recent fiscal year that ends before month t. The four regressions differ only in their treatment of fixed effects. Heteroskedasticity-robust t-statistics clustered by sector $\times$ month are in parentheses, where "sector" is defined as Morningstar style category. Data are from 1979–2011. There are 282,738 fund-month observations in the panel.

	Month Fixed Effects	
Fund Fixed Effects	No	Yes
Yes	0.00125	0.00118
	(6.67)	(7.08)
No	0.00043	0.00039
	(2.05)	(2.04)

Table II: Heterogeneity in the Turnover-Performance Relation

This table shows how the slope of fund performance on lagged turnover varies across funds. Each panel contains results from two regressions, one without controls, one with. The dependent variable in all regressions is $R_{i,t}$, fund i's net return plus expense ratio minus Morningstar's designated benchmark return in month t. We tabulate the slope coefficients for $FundTurn_{i,t-1}$ interacted with three dummy variables for the categories denoted in each panel's first row. All regressions include fund fixed effects. The specifications with controls also include $FundTurn_{i,t-1}$ interacted with the following variables: dummies for small-cap and large-cap funds (except in Panel A), dummies for growth and value (except in Panel B), dummies for small and large fund size (except in Panel C), and dummies for low and high expense ratio (except in Panel D). The tabulated slopes in specifications with controls in Panel A (for example) can therefore be interpreted as the slopes for a medium-sized, medium-expense ratio, blend fund. Heteroskedasticity-robust t-statistics clustered by sector × month are in parentheses, where "sector" is defined as Morningstar style category. Data are from 1979–2011.

Panel A: Stock Size Categories				
Small Cap	Mid Cap	Large Cap	Small - Large	Controls
0.00302	0.00114	0.00100	0.00202	No
(7.60)	(3.38)	(4.17)	(4.49)	
0.00171	0.00014	0.00025	0.00145	Yes
(3.57)	(0.35)	(0.85)	(3.17)	
Panel B: Stock Value-Growth Categories				
Growth	Blend	Value	Growth–Value	Controls
0.00155	0.00111	0.00184	-0.00029	No
(5.61)	(4.85)	(4.35)	(-0.54)	
0.00062	0.00014	0.00077	-0.00016	Yes
(1.56)	(0.35)	(1.42)	(-0.29)	
Panel C: Fund Size Categories				
Small	Medium	Large	Small–Large	Controls
0.00195	0.00089	0.00037	0.00158	No
(7.86)	(4.12)	(1.24)	(4.51)	
0.00113	0.00014	-0.00025	0.00138	Yes
(2.76)	(0.35)	(-0.59)	(3.49)	
Panel D: Fund Expense Ratio Categories				
High	Medium	Low	High–Low	Controls
0.00161	0.00099	0.00077	0.00084	No
(6.02)	(5.02)	(3.60)	(3.09)	
0.00065	0.00014	0.00003	0.00062	Yes
(1.47)	(0.35)	(0.08)	(2.05)	

Table III: Properties of Fund Turnover and Performance Across Fund Categories

This table contains summary statistics on fund turnover ($FundTurn$) and returns in the full sample (Panel A) as well as in categories of funds formed on Morningstar's stock-size categories (Panel B), Morningstar's value-growth categories (panel C), monthly terciles of fund assets (Panel D), and monthly terciles of fund expense ratios (Panel E). When counting funds per category, we assign each fund to the category in which it most often appears. The volatility of $FundTurn$ equals the standard deviation of fund-demeaned $FundTurn$. The next column shows the correlation between the current and previous year's fund-demeaned turnover, pooling all fund/years. For the $FundTurn$ variables, we test for differences across fund categories by reporting the heteroskedasticity-robust t-statistics clustered by fund and year. For return variables, we test for differences across categories by reporting the heteroskedasticity-robust t-statistic clustered by Sector $\times$ month and (since we omit fund fixed effects) fund. Data are from 1979–2011.

Funds	Number	Fund turnover (fraction/year)			Average benchmark-adjusted return (%/month)	
included	of funds	Average	Volatility	Autocorr.	Gross	Net
			Panel A: Full Sample			
All	2721	0.850	0.450	0.507	0.0389	-0.0585
			Panel B: Stock Size Categories			
Small-Cap	572	0.914	0.418	0.479	0.1913	0.0896
Mid-Cap	597	0.974	0.485	0.511	-0.0068	-0.1074
Large-Cap	1291	0.758	0.425	0.507	0.0161	-0.0783
Small – Large		0.156	-0.007	-0.028	0.1752	0.1679
(t-statistic)		(4.62)	(-0.34)	(-0.92)	(3.81)	(3.75)
			Panel C: Stock Value-Growth Categories			
Growth	1016	1.056	0.499	0.504	0.1097	0.0136
Blend	803	0.772	0.434	0.534	0.0019	-0.0939
Value	639	0.611	0.335	0.424	0.0154	-0.0834
Growth – Value		0.445	0.164	0.081	0.0943	0.0971
(t-statistic)		(15.41)	(9.04)	(2.37)	(2.20)	(2.28)
			Panel D: Fund Size Categories			
Small	1258	0.908	0.478	0.422	0.0519	-0.0489
Medium	802	0.897	0.464	0.496	0.0533	-0.0525
Large	659	0.759	0.410	0.603	0.0146	-0.0761
Small – Large		0.149	0.068	-0.181	0.0373	0.0272
(t-statistic)		(5.39)	(3.95)	(-5.35)	(2.48)	(1.81)
			Panel E: Fund Expense Ratio Categories			
High	1019	0.978	0.511	0.485	0.0812	-0.0619
Medium	848	0.837	0.422	0.519	0.0287	-0.0705
Low	854	0.730	0.377	0.492	0.0074	-0.0611
High – Low		0.248	0.134	-0.006	0.0738	-0.0009
(t-statistic)		(7.75)	(6.86)	(-0.20)	(4.58)	(-0.05)

Table IV: Correlations of Average Turnover Across Fund Categories

This table shows the pairwise correlations between the time series plotted in Figure 1. The table's four panels correspond to Figure 1's four panels.

Stock Size	S	M	L	Stock Value-Growth	G	B	V
Small	1.00			Growth	1.00		
Mid	0.59	1.00		Blend	0.76	1.00	
Large	0.67	0.18	1.00	Value	0.80	0.62	1.00

Fund Size	S	M	L	Fund Expense Ratio	L	M	H
Small	1.00			Low	1.00		
Medium	0.54	1.00		Medium	0.76	1.00	
Large	0.52	0.44	1.00	High	0.74	0.74	1.00

Table V: Commonality in Fund Turnover

The dependent variable is turnover of fund i in the fiscal year that includes month t ($FundTurn_{i,t}$). The regressors are averages of turnover across funds $j \neq i$ in month t. $AvgTurn$ is the average across all funds, $AvgTurn\_Stock\_Size$ is the average across funds in the same stock-size category as fund i, $AvgTurn\_Stock\_VG$ across funds in the same stock value-growth category as fund i, $AvgTurn\_Fund\_Size$ across funds in the same size-tercile category as fund i, and $AvgTurn\_Fund\_Exp$ across funds in the same expense ratio-tercile category as fund i. $AvgTurnSim$ is the average across funds in the same stock-size, fund-size, and expense-ratio category as fund i. All regressions include fund fixed effects. We compute robust t-statistics clustering by fund and calendar year. Data are from 1979–2011.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$AvgTurn$	0.651							0.425
	(8.65)							(5.71)
$AvgTurn\_Stock\_Size$		0.547				0.181		
		(8.94)				(2.21)		
$AvgTurn\_Stock\_VG$			0.452			0.0971		
			(6.65)			(1.39)		
$AvgTurn\_Fund\_Size$				0.629		0.287		
				(10.65)		(4.02)		
$AvgTurn\_Fund\_Exp$					0.577	0.275		
					(11.15)	(4.13)		
$AvgTurnSim$							0.351	0.267
							(9.54)	(7.66)
Observations	303,933	270,449	270,449	303,564	282,738	259,714	259,234	259,234
Within-fund R^2 (%)	1.28	1.65	1.20	1.77	1.80	2.62	1.84	2.29

Table VI: What Explains Turnover?

The dependent variable in columns 1–4 is $FundTurn_{i,t}$, fund i's turnover during the fiscal year that includes month t. The dependent variable in columns 5–8 is $AvgTurn_t$, the average turnover across funds in month t. $Sentiment_t$, measured in month t, is from Baker and Wurgler (2007, JEP). $Volatility_t$ is the cross-sectional standard deviation of CRSP stock returns in month t. $Liquidity_t$ is the month-t level of aggregate liquidity from Pástor and Stambaugh (2003). $Business\ Cycle_t$ is the Chicago Fed National Activity Index in month t. $Market\ Return_t$ is the return on the CRSP market portfolio from months $t-12$ to month $t-1$. $Time\ Trend_t$ equals the number of months since January 1979. We estimate columns 1–4 as an OLS panel regression with fund fixed effects, clustering by fund and calendar year. We estimate columns 5–8 as a Newey-West time-series regression using 60 months of lags. Columns 1–4 show within-fund R^2 values. $R^2 - R^2$(trend only) equals the R^2 from the given regression minus the R^2 from a regression on the time trend only. Data are from 1979–2011. t-statistics are in parentheses.

	Dependent variable: $FundTurn_{it}$				Dependent variable: $AvgTurn_t$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Sentiment_t$	0.0359			0.0232	0.0531			0.0487
	(3.27)			(2.87)	(3.17)			(4.65)
$Volatility_t$		0.747		0.540		0.938		0.809
		(7.69)		(5.56)		(7.23)		(7.98)
$Liquidity_t$			-0.192	-0.0869			-0.212	-0.138
			(-4.53)	(-3.88)			(-4.14)	(-4.58)
$Business\ Cycle_t$				-0.0122				-0.00334
				(-1.84)				(-0.66)
$Market\ Return_t$				-0.0365				0.0171
				(-1.34)				(0.34)
$Time\ Trend_t$	0.0000	-0.0001	-0.0001	-0.0001	0.0006	0.0004	0.0005	0.0005
	(0.06)	(-0.53)	(-0.83)	(-0.47)	(5.21)	(3.88)	(3.44)	(5.20)
R^2	0.002	0.008	0.001	0.010	0.524	0.541	0.377	0.677
$R^2 - R^2$(trend only)	0.002	0.008	0.001	0.010	0.171	0.188	0.024	0.324
Observations	263,895	272,413	272,413	263,895	372	382	382	372

Table VII: Relation Between Fund Performance and Average Turnover

The dependent variable in each regression model is $R_{i,t}$, fund i's net return plus expense ratio minus Morningstar's designated benchmark return in month t. $AvgTurnSim_{i,t-1}$ is the lagged average turnover across funds $j \neq i$ that are in the same stock-size, fund-size, and expense-ratio category as fund i. $AvgTurn_{i,t-1}$ is the lagged average turnover across funds $j \neq i$. $FundTurn_{i,t-1}$ is fund i's lagged turnover. All regressions include fund fixed effects. Heteroskedasticity-robust t-statistics clustered by sector $\times$ month are in parentheses. Data are from 1979–2011.

	(1)	(2)	(3)	(4)	(5)	(6)
$AvgTurnSim_{i,t-1}$	0.00210			0.00184		0.00158
	(3.29)			(2.76)		(2.92)
$AvgTurn_{i,t-1}$		0.00359			0.00339	0.00133
		(1.52)			(1.42)	(0.53)
$FundTurn_{i,t-1}$			0.00125	0.00135	0.00118	0.00134
			(6.67)	(7.30)	(6.88)	(7.54)
Observations	281,406	306,897	282,738	259,234	282,738	259,234

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