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DO FUNDS MAKE MORE WHEN THEY TRADE MORE?

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ABSTRACT

We model optimal fund turnover in the presence of time-varying profit opportunities. Our model predicts a positive relation between an active fund's turnover and its subsequent benchmark-adjusted return. We find such a relation for equity mutual funds. This time-series relation between turnover and performance is stronger than the cross-sectional relation, as the model predicts. Also as predicted, the turnover-performance relation is stronger for funds trading less-liquid stocks, such as small-cap funds. Turnover has a common component that is positively correlated with proxies for stock mispricing, consistent with funds exploiting time-varying opportunities. Turnover's common component helps predict fund returns.

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1. Introduction

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 net 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 optimally chosen turnover and subsequent return.

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 0.65% 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 weak positive cross-sectional relation, marginally significant at best.

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

[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).

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 as much as they dampen the cross-sectional relation, where 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 trade in smaller dollar amounts.

We find a stronger turnover-performance relation as well for funds charging higher fees. This result has a skill-based interpretation, under the plausible assumption that funds with greater skill charge higher fees. If a less-skilled fund trades on profit opportunities that are not really there, then some of the fund's turnover is unrelated to expected future return. The turnover-performance relation is therefore weaker for less-skilled funds.

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 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 average turnover is associated with a 0.71% per year increase in fund performance. The relation is even stronger when average turnover is computed only across similar 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. The common component of individual fund turnover—average turnover—helps capture a fund's true turnover and thus helps to predict the fund's performance. Measurement error can also explain our finding that a fund's performance is predicted even more strongly by the average turnover of similar funds. Since commonality in turnover is greater among similar funds, average turnover of similar funds is particularly useful in capturing a fund's true turnover in the presence of measurement error.

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. 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] Our finding of a significant positive time-series relation between turnover and performance provides novel evidence of skill.

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 better 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

[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).

different from ours. Second, all of them identify cross-sectional relations between activity and performance, whereas we establish a time-series relation.

Given this time-series perspective, 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.

While we analyze funds' ability to time their turnover, others have investigated the value of active fund management by examining different fund actions. Chen, Jegadeesh, and Wermers (2000) find that stocks recently bought by funds in aggregate outperform stocks recently sold, suggesting that funds have stock-picking skill. Baker et al. (2010) find that much of this outperformance takes place around corporate earnings announcements, indicating one likely source of the funds' skill. Cohen, Coval, and Pástor (2005) find that funds whose portfolio decisions are similar to those of other funds with strong track records perform better. Alexander, Cici, and Gibson (2007) show that funds' valuation-motivated buys (i.e., large stock buys concurrent with heavy fund outflows) outperform benchmarks whereas liquidity-motivated buys do not. Cohen, Frazzini, and Malloy (2008) find that fund managers perform better when they trade shares of firms they are connected to through their educational networks. Like us, all of these studies report that active management adds value, but they examine different dimensions of fund skill. Our finding that funds are able to successfully time their trading activity seems new in the literature.

Lastly, 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 2 presents our model, which implies a positive relation between a fund's turnover and subsequent return. Section 3 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 4 explores differences in the strength of the time-series relation across categories of funds differentiated by size, fees, and investment styles. Section 5 analyzes the common component of fund turnover and its predictive power for fund returns. Section 6 concludes.

2. 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.

2.1 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 π_t. 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 $\gamma \geq 0$. 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.

2.2 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.[4] 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

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

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

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

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 net 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

[4] One justification for this assumption is that a higher profit before fees essentially provides the fund with a higher fee, if fund flows result in zero net alpha provided to investors, as in Berk and Green (2004).

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.[5]

2.3 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 a constants and $|\rho| < 1$.[6] Taking the expectation of the right-hand side of 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

[5] 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.

[6] 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.

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.

2.4 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

$$h = c\left(\frac{\theta}{1-\theta}\right). \tag{15}$$

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 the next section are consistent with the model's implied difference between the time-series and cross-sectional slopes, given in equation (16).

3. 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

$$R_{i,t} = a_i + b_i X_{i,t-1} + \epsilon_{i,t} \ , \tag{17}$$

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 $t-1$.[7] 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 profit opportunities arise, i.e., variation in π_t in equation (1). Although the regression in equation (17) 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 $GrossR_{i,t}$, 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

[7] 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 (17).

the most recent fiscal year that ends before month t. This measure is defined as

$$FundTurn_{i,t-1} = \frac{\min\left(buys_{i,t-1}, sells_{i,t-1}\right)}{\text{avg}\left(TNA_{i,t-1}\right)} \ , \tag{18}$$

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 3.2.1. We winsorize $FundTurn_{i,t-1}$ at the 1st and 99th percentiles.

To increase the power of our inferences in equation (17), we estimate a panel regression that imposes the restriction

$$b_1 = b_2 = \cdots = b \ . \tag{19}$$

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 (17) when the restriction in (19) is imposed across all funds. The regression specification combining equations (17) and (19), 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.

3.1. Time-series versus cross-sectional estimates

Table 1 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 (17) and (19):

$$R_{i,t} = a_i + bX_{i,t-1} + \epsilon_{i,t} \ . \tag{20}$$

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.

The estimate $\widehat{b}$ in the top left cell of Table 1 is positive and highly significant, with a t-statistic of 6.63. 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 0.438. Therefore, the estimated slope of 0.00123 implies that a one-standard-deviation increase in a fund's turnover translates to an increase in annualized expected return of 0.65% ($= 0.00123 \times 0.438 \times 1200$). This number is substantial, in that it is comparable in magnitude to funds' overall average annualized $R_{i,t}$, equal to 0.60%. In other words, conditioning fund returns on turnover implies fluctuations in the conditional expected return that are of first-order economic importance, often as large as the unconditional expected return.

The top right cell of Table 1 reports $\widehat{b}$ from a panel regression that includes both fund and month fixed effects. The resulting estimate, 0.00106, is only slightly smaller than its counterpart in the top left cell, and it is similarly significant ($t = 6.77$). 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 (19) but also

$$a_1 = a_2 = \cdots = a \ . \tag{21}$$

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 1 thus reflects both cross-sectional and time-series variation. This estimate is positive, 0.00040, but only marginally significant, with a t-statistic of 1.92.

The bottom right cell of Table 1 reports $\widehat{b}$ from a purely cross-sectional specification, in which fund fixed effects a_i are replaced by month fixed effects a_t:

$$R_{i,t} = a_t + bX_{i,t-1} + \epsilon_{i,t} \ . \tag{22}$$

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 (22), 0.00030, is positive but the

t-statistic is only 1.61. The point estimate is smaller than in the bottom left cell, which shows that isolating cross-sectional variation further weakens the turnover-performance relation.

Table 1 clearly shows that the turnover-performance relation is stronger in the time series than in the cross section. Recall from our model that we expect such a result, with the difference between the time-series and cross-sectional slopes given by equation (16). In fact, the difference between these slopes in Table 1 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 1 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 1 from the time-series slope in the upper-left cell, multiplying by 12, gives $12(0.00123 - 0.00030) = 0.0112$, which rounds to 0.01, just like the above implied difference of 0.0086.[8]

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

3.2. Robustness

The positive turnover-performance relation documented above, 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

[8]The time-series and cross-sectional slopes when 12-month return is regressed on 12-month turnover equal 0.0200 and 0.0107, as reported in the online appendix. The difference in these slopes, 0.0093, is also quite close to the above implied difference of 0.0086.

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.[9] 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 1 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 1 are -0.51 and -1.07). 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 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 (20). 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 (20), the resulting slope on $X_{i,t-1}$ and its t-statistic are virtually unchanged.

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

[9] 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.

analysis, such as fund returns, fund size, industry 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 1. 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.[10]

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 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).[11] To test for such long-horizon effects, we add two more lags of $FundTurn$ to the right-hand side of regression (20). 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.

[10]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 $FundTurn$.

[11]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.

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 (20).

The positive turnover-performance relation emerges not only from the panel regression in Table 1, which imposes the restriction (19), but also from fund-by-fund regressions. For each fund i, we estimate the slope b_i from the time-series regression in equation (17) 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 1, as shown in equation (37).[12] 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.

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.[13] 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

[12]The cross-sectional correlation between $\widehat{b}_i$ and the length of fund i's track record is insignificant at 0.02, indicating that the turnover-performance relation is no stronger for longer-lived funds.

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

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.[14] 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 1 remain positive and significant, with t-statistics in excess of 3.2.

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 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.[15] 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 all of our main conclusions are robust to using the 2000–2011 subperiod. For example, the time-series turnover-performance relation in Table 1 remains positive and significant, with t-statistics of 4.37 and 3.74 in the top row. In the online appendix, we report the counterparts of all of our tables estimated in the 2000–2011 subperiod.

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

[15] 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*.

3.2.1. Measuring Turnover

We measure fund turnover by its official SEC definition from equation (18). 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 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.[16]

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.

[16]Our results are also broadly consistent with those of Alexander, Cici, and Gibson (2007) who find that future returns of funds' discretionary trades are higher than those of flow-induced trades.

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.

3.2.2. 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. Morningstar assigns funds to categories by relying heavily on the funds' reported portfolio holdings. Since these 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 1 continue to be highly significant, with t-statistics of 7.09 and 8.27, while the slopes in the bottom row remain insignificant. 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 (2014), 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 1 continue to be highly significant, with t-statistics ranging from 5.93 to 9.34. The slope coefficients in the bottom row remain insignificant, except 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. That is, under those two benchmark models, the positive turnover-performance relation emerges also from the cross-section, but in general, the relation appears only in the time series.

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 1, we find that the slope estimates in the bottom

row are insignificant while the slopes in the top row are highly significant, with t-statistics of about 7.6.

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.

4. 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. In our sample, these two style classifications are held constant over a fund's history.

Panels A through D of Table 2 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 (20) 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

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 2 reveals a significantly positive turnover-performance relation in eight of the nine no-controls regressions. The only exception is large funds, having a t-statistic of 1.46 (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. The relation is significant for small-cap funds, small funds, and high-fee funds even when we include controls, thereby characterizing funds whose other three characteristics are in the middle category.

We also see in Table 2 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 0.00205 ($t = 3.53$), nearly seven times the large-cap slope of 0.00030 ($t = 0.81$). The differences associated with fund size and fees are similarly large. 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 2, 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 3 shows that the turnover of small-cap funds has significantly lower autocorrelation 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 2 that small-cap funds indeed have a higher estimated slope.

A similar interpretation applies to the results in Panel C of Table 2, 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 3 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.

Recall from Panel B of Table 2 that 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 3 that turnover for growth funds has a significantly higher autocorrelation than does turnover of value funds.

The differences in turnover-performance slopes related to expense ratio, reported in Panel D of Table 2, must be interpreted outside our model, in which expense ratio does not appear. Expense ratio, closely related to the management fee rate, 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.[17] Also, we find a higher slope for high-fee funds regardless of whether we condition on fund size by including controls in Panel D. Less-skilled (and thus lower-fee) funds are likely to have a lower turnover-performance slope, because they tend to make two mistakes. First, they sometimes trade too much, perceiving profit opportunities that do not really exist. Consistent with this idea, Christoffersen and Sarkissian (2011) argue that overconfidence sometimes leads mutual funds to trade too much.[18] Second, less-skilled funds sometimes trade too little, failing to perceive profit opportunities that truly exist. Because of these mistakes, some of the time variation in a less-skilled fund's turnover is unrelated to time variation in true profit opportunities, producing a weaker turnover-performance relation. If a fund is so unskilled that its turnover

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

[18]Christoffersen and Sarkissian (2011) find that excessive trading is more prevalent among fund managers working in major financial centers. They also find that excess turnover declines with experience, consistent with overconfident managers gradually learning their true ability. While the authors' focus is on demographic determinants of turnover, they also report a mixed relation between turnover and performance based on panel regressions similar to ours but without fund fixed effects.

is pure noise, the turnover-performance slope is zero.

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 a significantly stronger turnover-performance relation than low-skill funds. These results, which are consistent with those in Table 2 based on fees, are in the online appendix.

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 40% larger in magnitude for direct-sold funds, but the slope difference is not statistically significant (the p-value is 15%). While this evidence is inconclusive, it 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 3 are also consistent with the model, in two ways. In each of the four panels of Table 3, the average gross return of the top category is significantly greater than the bottom category. The same is true for two other quantities that our model predicts to be related to expected gross return: average turnover (Table 3) and the turnover-performance slope (Table 2). The observed link between the average gross return and average turnover 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 estimate in Table 1.[20] The observed link to the turnover-performance slope is consistent with equations (13) through (15). 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. Interestingly, the only top-minus-bottom difference for which the slope in Table 2 is insignificant, growth minus value, is also the only difference for which the average gross return in Table 3 is only marginally

[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.

significant, which jibes well with the model.

5. The Common Component of 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 5.1, we analyze comovement in fund turnover. In Section 5.2, we investigate the determinants of the common component of turnover. Finally, in Section 5.3, we study the predictive power of the common component for fund performance.

5.1. Commonality in 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.

Figure 1 plots the time series of the category-level average turnover over the 1979-2011 period. 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 59%. We observe similar correlations, ranging from 52% to 61%, 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 4. 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.

Panel B of Figure 1 provides more evidence on the result from Table 3 that growth funds turn over 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.

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 5. The slope coefficient from the regression of $FundTurn$ on $AvgTurn$ is 0.65 ($t = 8.65$), indicating strong evidence of commonality in turnover.

The evidence of commonality strengthens further when we add category-level average turnover to the right-hand side of 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 both $AvgTurn$ and $AvgTurn\_Stock\_Size$, the category-level average is highly significant ($t = 5.27$), the sum of the slopes on the two averages is again 0.65, and the R^2 increases by almost half. 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 ($AvgTurn\_Fund\_Exp$). While the value-growth average is insignificant when added to the above regression, the other two averages produce results very similar to those obtained for the stock-size average: 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.

category-level average is highly significant, the sum of the slopes on the two averages is a bit larger than 0.65, and the R^2 increases by almost half. 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 observed earlier.) When added to the above regression, this variable comes in highly significant ($t = 7.35$), the sum of the slopes on $AvgTurn$ and $AvgTurnSim$ is 0.68, and the R^2 almost doubles. This evidence, which is reported in Table 5, shows that commonality in turnover is especially strong among funds with similar characteristics.

5.2. 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. Consistent with this prediction, time-series regressions of both $FundTurn_{i,t}$ and $AvgTurn_t$ on $Sentiment_t$ produce significantly positive slope coefficients ($t = 3.35$ and $t = 3.17$, respectively), as shown in columns 1 and 5 of Table 6. 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. As reported in the last row of of Table 6, 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.

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

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

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 ($t = 7.78$ and $t = 7.23$, respectively), as shown in columns 2 and 6 of Table 6. 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 accompanied 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 ($t = -4.55$ and $t = -4.14$, respectively), reported in columns 3 and 7 of Table 6. 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 very similar to when included just by itself. These all-inclusive regressions, reported in columns 4 and 8 of Table 6, 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

[24] If we exclude the time trend from the regressions, we find results similar to those reported in Table 6. *Volatility* and *Liquidity* continue to enter significantly with the same signs as in Table 6, 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*.

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 of six variables that include NYSE turnover. However, when we add market turnover to the all-inclusive specification in column 8 of Table 6, 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 6.

5.3. 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 performance can be motivated directly within our model. 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^*. There could also be other reasons why a fund's observed turnover could differ from its true, optimally chosen value. In other words, we observe

$$\tilde{X}_t = X_t^* + u_t \ , \tag{23}$$

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

$$X_t^* = \beta_X \overline{X}_t + \phi_t \ , \tag{24}$$

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 $\overline{X}_t$:

$$R_{t+1} = \hat{\theta}_0 + \hat{\theta}_1 \tilde{X}_t + \hat{\theta}_2 \overline{X}_t + e_{t+1} \ . \tag{25}$$

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

$$\theta_1 = \left(\frac{\sigma_\phi^2}{\sigma_\phi^2 + \sigma_u^2} \right) b \tag{26}$$

$$\theta_2 = \left(\frac{\beta_X \sigma_u^2}{\sigma_\phi^2 + \sigma_u^2} \right) b \ . \tag{27}$$

Both θ_1 and θ_2 are positive as long as b from equation (11) and β_X from equation (24) are positive, which is consistent with the data (see Tables 1 and 5). 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.

We find such a role in the data. We run a panel regression of the gross benchmark-adjusted fund return ($GrossR_{i,t}$) on average lagged turnover, with fund fixed effects. We denote average lagged turnover, or the average of $FundTurn_{j,t-1}$ across $j \neq i$, by $AvgTurn_{t-1}$.[25] Column 1 of Table 7 reports the slope from the regression of $GrossR_{i,t}$ on $AvgTurn_{t-1}$.[26] The slope is positive and significant ($t = 2.25$), indicating that the common component of fund trading helps predict individual fund performance. The magnitude of the estimate, 0.00784, implies substantial economic significance. Given the time-series standard deviation of $AvgTurn_{t-1}$, 0.076, a one-standard-deviation increase in the variable translates to an increase in expected return of 0.71% per year ($= 0.00784 \times 0.076 \times 1200$).

The information in $AvgTurn_{t-1}$ about a fund's subsequent performance is undiminished by conditioning on the fund's own turnover. Column 4 of Table 7 shows that the coefficient and t-statistic for $AvgTurn_{t-1}$ are little changed by controlling for $FundTurn_{i,t-1}$. Similarly, the significance of the slope on $FundTurn_{i,t-1}$ is little changed by controlling for $AvgTurn_{t-1}$. The fund's performance is predictable by both 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 (25).

[25] We omit the i subscript from $AvgTurn_{i,t-1}$ because excluding fund i from the average makes very little difference. Note that $AvgTurn_{t-1}$ uses only information available before month t because it is the average of turnovers computed over 12-month periods that end before month t. It is thus reasonable to use $AvgTurn_{t-1}$ 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 5.1, we use the notation $AvgTurn_t$ to 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 5.1 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 5.1 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 7 exclude a time trend, but the results are very similar if we include one.

The above discussion suggests the predictive power of average turnover is due to commonality in turnover. Since this commonality is stronger among funds with similar characteristics (recall Table 5), the predictive power of average turnover might improve if the average is computed across only similar funds. To examine this hypothesis, we regress $GrossR_{i,t}$ on $AvgTurnSim_{t-1}$.[27] Column 2 of Table 7 shows that the slope on $AvgTurnSim_{t-1}$ is positive and significant ($t = 3.69$), and column 5 shows that it remains so when controlling for $FundTurn_{i,t-1}$. In column 6, we consider the regression in which both average turnovers are included, along with $FundTurn_{i,t-1}$. In this horserace, $AvgTurnSim_{t-1}$ remains positive and significant whereas $AvgTurn_{t-1}$ turns insignificant. The variable that better captures commonality in turnover is thus more important in predicting fund performance.

We have shown that a fund's performance is predictable not only by the fund's own turnover but also by the average turnover of other funds, especially similar funds. We have motivated this result in the context of our model, based on the commonality in turnover and measurement error. The turnover of other funds can also predict performance for other reasons that are outside the model. For example, in the model, funds always trade optimally, but suboptimal trading can also create a predictive role for $AvgTurn_{t-1}$, as we explain next.

Suppose that funds trade suboptimally, so that only a fraction of a typical fund's turnover involves exploiting true profit opportunities. Also suppose that funds' profit opportunities are positively correlated. This setting can arise, for example, if some stocks are mispriced while others are not, funds trade both types of stocks (the latter erroneously), and the degree of mispricing in the former stocks varies over time in a way that many funds can exploit. In this setting, as long as funds' deviations from optimal trading are approximately uncorrelated, heavier trading by other funds indicates more mispricing. Therefore, not only $FundTurn_{i,t-1}$ but also $AvgTurn_{t-1}$ can predict performance. $FundTurn_{i,t-1}$ is higher—and fund i's subsequent performance is better—when fund i's own manager identifies more profit opportunities. When many managers identify such opportunities, $AvgTurn_{t-1}$ is higher, and there is more mispricing in general. 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.

The same story can also explain why $AvgTurnSim_{t-1}$ drives out $AvgTurn_{t-1}$ in column 6 of Table 7. If trading by other funds signals the presence of greater mispricing, then heavier trading by funds similar to one's own could signal greater mispricing that is especially relevant. In other words, heavier trading by less-similar funds could be less relevant to one's own fund. This possibility is consistent with our evidence that the turnover of one's own

[27] As we did for $AvgTurn_{t-1}$, we exclude fund i from the average yet omit the i subscript.

fund typically comoves more with the turnover of similar funds.

6. 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 turnover and its subsequent benchmark-adjusted return. We find strong support for this implication in a comprehensive sample of 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 with higher fees, consistent with such funds having greater skill in identifying time-varying profit opportunities.

We provide strong evidence of commonality in mutual 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. The common component of turnover 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. Turnover's common component 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 true opportunities a fund does identify are likely to be more profitable when turnover's common component is high. Commonality in turnover is especially high among funds sharing similar characteristics, and a fund's performance is predicted even more strongly by the average turnover of similar funds.

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.

Our study could be extended in several directions. For example, while we relate funds' turnover to their future performance, it could also be interesting to relate turnover to fund flows. Such analysis would reveal whether fund investors are aware of turnover's ability to predict returns. In the Berk and Green (2004) model, investors respond to fund returns, but our results suggest that they might also benefit from responding to turnover. Another promising direction is to go beyond turnover and analyze the funds' trading activity in more detail. For example, one could analyze changes in fund holdings or adjust turnover for non-discretionary trading. Such analysis could potentially produce even more powerful predictors of future fund performance. Finally, finding exogenous variation in profit opportunities and funds' ability to exploit them would help identify any causal relations between fund performance, trading, and mispricing. We leave these challenges for future work.

Appendix.

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 1 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

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

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,

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

and the single-equation least-squares estimator,

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

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

$$\hat{b}_i = \frac{1}{\hat{\sigma}^2_{x_i}} \left(\frac{x_i' y_i}{m_i} - \bar{x}_i \bar{y}_i\right) \ , \tag{28}$$

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

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

and the least-squares estimator

$$\begin{bmatrix} \hat{a}_1 \\ \vdots \\ \hat{a}_N \\ \hat{b} \end{bmatrix} = (X'X)^{-1}X'y \ . \tag{29}$$

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

$$\hat{b} = \sum_{i=1}^{N} w_i \hat{b}_i \ , \tag{30}$$

where

$$w_i = \frac{m_i \hat{\sigma}_{x_i}^2}{\sum_{k=1}^{N} m_k \hat{\sigma}_{x_k}^2} \ . \tag{31}$$

Proof. First observe

$$\begin{aligned} X'X &= \begin{bmatrix} \iota_1' & 0 & \cdots & 0 \\ 0 & \iota_2' & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & & & \iota_N' \\ x_1' & x_2' & \cdots & x_N' \end{bmatrix} \begin{bmatrix} \iota_1 & 0 & \cdots & 0 & x_1 \\ 0 & \iota_2 & & \vdots & x_2 \\ \vdots & & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & \iota_N & x_N \end{bmatrix} \\ &= \begin{bmatrix} m_1 & 0 & \cdots & 0 & \iota_1'x_1 \\ 0 & m_2 & & \vdots & \iota_2'x_2 \\ \vdots & & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & m_N & \iota_N'x_N \\ \iota_1'x_1 & \iota_2'x_2 & \cdots & \iota_N'x_N & x'x \end{bmatrix} \\ &= \begin{bmatrix} D & v \\ v' & q \end{bmatrix} , \end{aligned} \tag{32}$$

and therefore

$$(X'X)^{-1} = \begin{bmatrix} D^{-1} + D^{-1}v(q - v'D^{-1}v)^{-1}v'D^{-1} & -D^{-1}v(q - v'D^{-1}v)^{-1} \\ -(q - v'D^{-1}v)^{-1}v'D^{-1} & (q - v'D^{-1}v)^{-1} \end{bmatrix} . \tag{33}$$

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

$$D^{-1}v = \begin{bmatrix} (\iota_1'x_1)/m_1 \\ \vdots \\ (\iota_N'x_N)/m_N \end{bmatrix} = \begin{bmatrix} \bar{x}_1 \\ \vdots \\ \bar{x}_N \end{bmatrix} = \bar{x} \ , \tag{34}$$

and that

$$q - v'D^{-1}v \ = \ x'x - \bar{x}'D\bar{x}$$

$$
\begin{aligned}
&= x_1'x_1 + \cdots + x_N'x_N - m_1\bar{x}_1^2 - \cdots - m_N\bar{x}_N^2 \\
&= m_1\left(\frac{x_1'x_1}{m_1} - \bar{x}_1^2\right) + \cdots + m_N\left(\frac{x_N'x_N}{m_N} - \bar{x}_N^2\right) \\
&= m_1\hat{\sigma}_{x_1}^2 + \cdots + m_N\hat{\sigma}_{x_N}^2 \ . \qquad (35)
\end{aligned}
$$

Also,

$$
X'y = \begin{bmatrix} \iota_1' & 0 & \cdots & 0 \\ 0 & \iota_2' & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & & & \iota_N' \\ x_1' & x_2' & \cdots & x_N' \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} \iota_1'y_1 \\ \iota_2'y_2 \\ \vdots \\ \iota_N'y_N \\ x'y \end{bmatrix} \ . \qquad (36)
$$

The last element of the pooled least-squares estimator in (29) can now be computed by pre-multiplying the vector in (36) by the last row of the matrix in (33), using (34) and (35) and then (28), to obtain

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

Q.E.D.

We can now interpret the time-series coefficient in the upper-left cell of Table 1. Let $\widehat{b}_i$ denote the estimated slope from the time-series regression in equation (17). Then $\widehat{b}$ from equation (20) is given by

$$
\widehat{b} = \sum_{i=1}^{N} w_i\widehat{b}_i \ , \qquad (37)
$$

where the weights w_i are given by

$$
w_i = \frac{T_i\widehat{\sigma}_{x_i}^2}{\sum_{n=1}^{N} T_n\widehat{\sigma}_{x_n}^2} \ , \qquad (38)
$$

T_i is the number of observations for fund i, and $\widehat{\sigma}_{x_i}^2$ 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 1. 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 (22) obeys the relation

$$
\widehat{b} = \sum_{t=1}^{T} w_t\widehat{b}_t \ , \qquad (39)
$$

where the weights w_t are given by

$$w_t = \frac{N_t \widehat{\sigma}^2_{x_t}}{\sum_{s=1}^{T} N_s \widehat{\sigma}^2_{x_s}} \ , \tag{40}$$

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 (39) 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 (39) 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).

Proof of Statements in Equations (26) and (27)

We now prove the statements related to equations (26) and (27) from Section 5.3. Combining equations (11) and (24) gives

$$R_{t+1} = a + b\beta_X \overline{X}_t + b\phi_t + \epsilon_{t+1} \ , \tag{41}$$

and combining (23) and (24) gives

$$\tilde{X}_t = \beta_X \overline{X}_t + \phi_t + u_t \ . \tag{42}$$

The probability limits of the estimated regression slope coefficients in (25) are given by

$$\begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} = \begin{bmatrix} \mathrm{Var}(\tilde{X}_t) & \mathrm{Cov}(\tilde{X}_t, \overline{X}_t) \\ \mathrm{Cov}(\tilde{X}_t, \overline{X}_t) & \mathrm{Var}(\overline{X}_t) \end{bmatrix}^{-1} \begin{bmatrix} \mathrm{Cov}(R_{t+1}, \tilde{X}_t) \\ \mathrm{Cov}(R_{t+1}, \overline{X}_t) \end{bmatrix} \ . \tag{43}$$

Let $\sigma^2_{\bar{X}}$ denote the variance of $\overline{X}_t$. Equations (41) and (42), along with the assumptions that all quantities on the right-hand sides of those equations are mutually uncorrelated, allow (43) to be simplified as

$$\begin{aligned} \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} &= \begin{bmatrix} \beta_X^2 \sigma^2_{\bar{X}} + \sigma^2_\phi + \sigma^2_u & \beta_X \sigma^2_{\bar{X}} \\ \beta_X \sigma^2_{\bar{X}} & \sigma^2_{\bar{X}} \end{bmatrix}^{-1} \begin{bmatrix} b(\beta_X^2 \sigma^2_{\bar{X}} + \sigma^2_\phi) \\ b\beta_X \sigma^2_{\bar{X}} \end{bmatrix} \\ &= \frac{1}{\sigma^2_{\bar{X}}(\sigma^2_\phi + \sigma^2_u)} \begin{bmatrix} \sigma^2_{\bar{X}} & -\beta_X \sigma^2_{\bar{X}} \\ -\beta_X \sigma^2_{\bar{X}} & \beta_X^2 \sigma^2_{\bar{X}} + \sigma^2_\phi + \sigma^2_u \end{bmatrix} \begin{bmatrix} b(\beta_X^2 \sigma^2_{\bar{X}} + \sigma^2_\phi) \\ b\beta_X \sigma^2_{\bar{X}} \end{bmatrix} \\ &= \begin{bmatrix} \left(\frac{\sigma^2_\phi}{\sigma^2_\phi + \sigma^2_u} \right) b \\ \beta_X \left(\frac{\sigma^2_u}{\sigma^2_\phi + \sigma^2_u} \right) b \end{bmatrix} \ . \end{aligned} \tag{44}$$

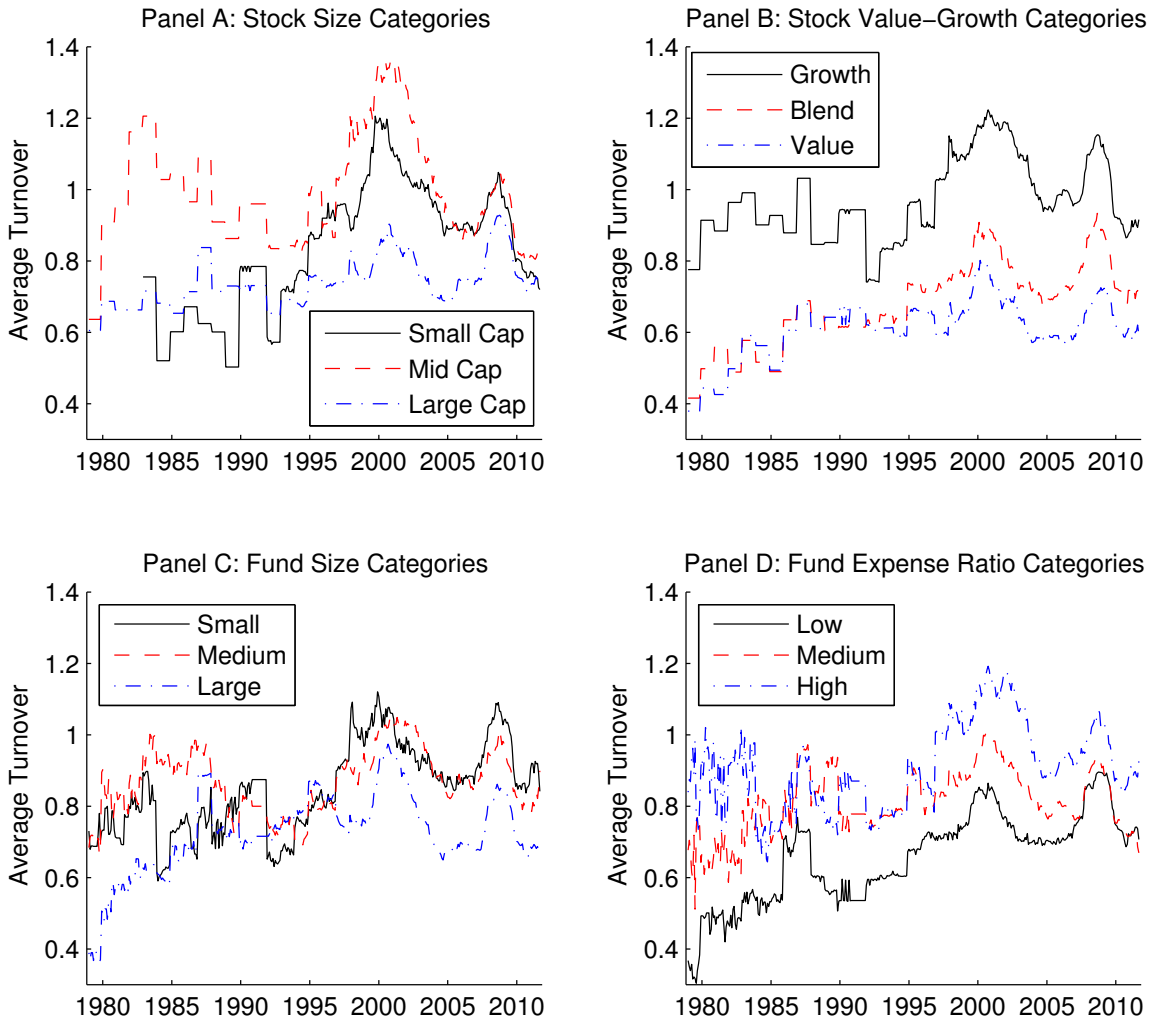

Figure 1. Average Turnover Across Fund Categories. Each panel splits funds into three categories and plots the time series of category-level average turnover. Average turnover in month t is the equal-weighted average turnover across category funds in the 12-month period that includes month t. Panel A 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. We drop months containing less than ten funds in the category, and we drop all months before those months to avoid discontinuous lines. Data are from 1979–2011.

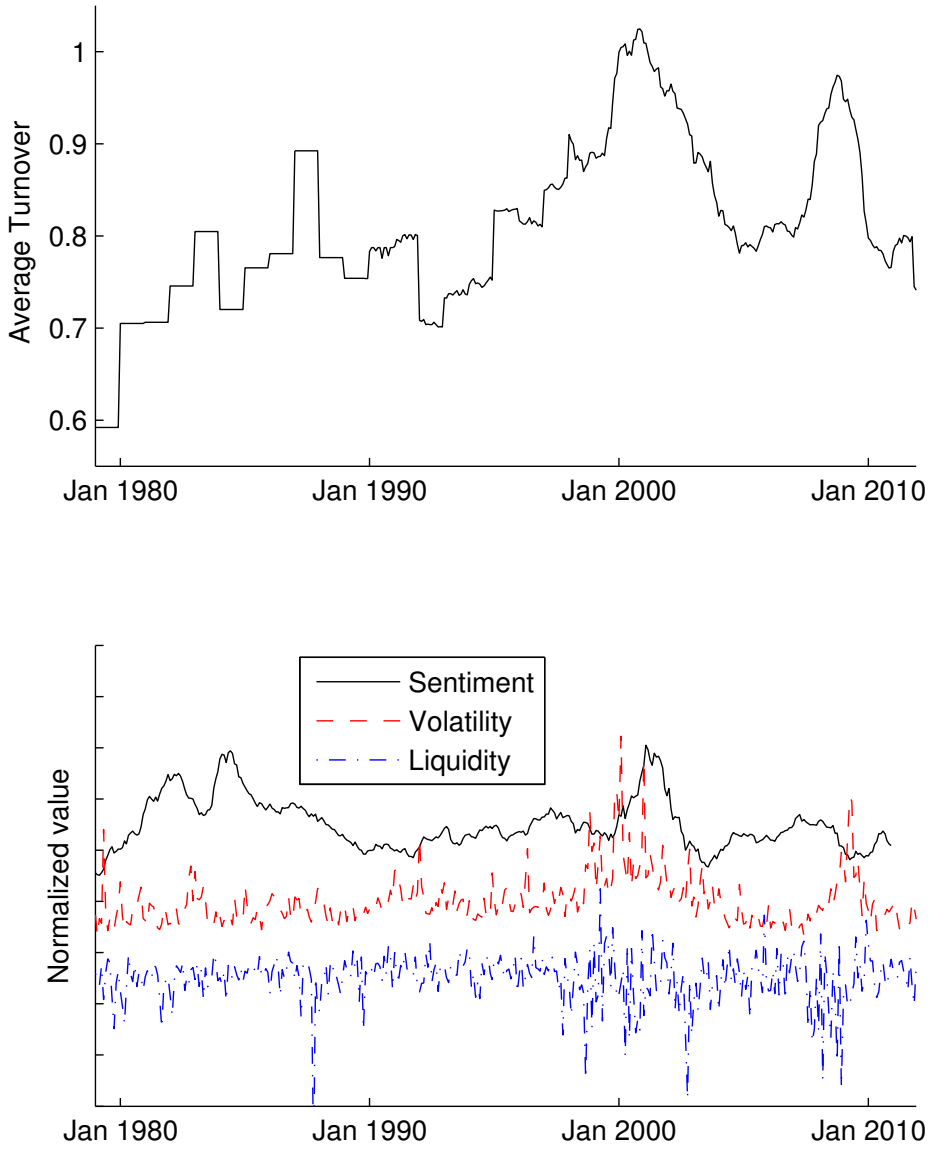

Figure 2. Average Turnover, Sentiment, Volatility, and Liquidity over time. Panel A plots the time series of $AvgTurn_t$, the equal-weighted average turnover across sample funds in the 12-month period that includes month t. Panel B plots the time series of *Sentiment* (from Baker and Wurgler, 2007);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

Table 1
Turnover-Performance Relation in the Cross Section and Time Series

The table reports the estimated slope coefficients from four different panel regressions of $GrossR_{i,t}$ on $FundTurn_{i,t-1}$. $GrossR_{i,t}$ 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 × month are in parentheses, where "sector" is defined as Morningstar style category. Data are from 1979–2011. There are 285,897 fund-month observations in the panel.

	Month Fixed Effects	
Fund Fixed Effects	No	Yes
Yes	0.00123	0.00106
	(6.63)	(6.77)
No	0.00040	0.00030
	(1.92)	(1.61)

Table 2: 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 $GrossR_{i,t}$, 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. The dummy variables vary within funds in Panels C and D, so we include these dummies as additional regressors. 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 can therefore be interpreted as the slopes for a medium-sized, medium-expense ratio, blend fund in Panel A (for example). 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
0.00313	0.00143	0.00091	0.00222	No
(5.87)	(2.88)	(4.72)	(3.92)	
0.00205	0.00056	0.00030	0.00175	Yes
(3.53)	(1.08)	(0.81)	(3.05)	
Panel B: Stock Value-Growth Categories				
Growth	Blend	Value	Growth–Value	Controls
0.00147	0.00141	0.00125	0.00021	No
(5.06)	(5.45)	(4.66)	(0.54)	
0.00070	0.00056	0.00061	0.00009	Yes
(1.28)	(1.08)	(1.23)	(0.24)	
Panel C: Fund Size Categories				
Small	Medium	Large	Small–Large	Controls
0.00186	0.00086	0.00043	0.00143	No
(7.56)	(3.74)	(1.46)	(4.11)	
0.00143	0.00056	0.00030	0.00113	Yes
(2.69)	(1.08)	(0.54)	(2.82)	
Panel D: Fund Expense Ratio Categories				
High	Medium	Low	High–Low	Controls
0.00170	0.00094	0.00058	0.00112	No
(6.38)	(4.62)	(2.84)	(4.06)	
0.00130	0.00056	0.00034	0.00096	Yes
(2.35)	(1.08)	(0.65)	(3.35)	

Table 3: 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 included	Number of funds	Fund turnover (fraction/year)			Average benchmark-adjusted return (%/month)	
		Average	Volatility	Autocorr.	Gross	Net
Panel A: Full Sample						
All	2722	0.850	0.450	0.507	0.0499	-0.0465
Panel B: Stock Size Categories						
Small-Cap	545	0.932	0.405	0.440	0.1770	0.0775
Mid-Cap	533	1.017	0.513	0.528	-0.0055	-0.0966
Large-Cap	1399	0.762	0.425	0.506	0.0443	-0.0535
Small – Large		0.170	-0.020	-0.066	0.1327	0.1310
(t-statistic)		(4.75)	(-1.00)	(-2.11)	(2.31)	(2.34)
Panel C: Stock Value-Growth Categories						
Growth	1121	1.016	0.504	0.520	0.1084	0.0153
Blend	779	0.741	0.398	0.504	0.0260	-0.0748
Value	577	0.636	0.344	0.410	0.0089	-0.0877
Growth – Value		0.381	0.160	0.110	0.0995	0.1030
(t-statistic)		(12.82)	(7.69)	(2.10)	(1.90)	(1.98)
Panel D: Fund Size Categories						
Small	1260	0.908	0.478	0.422	0.0673	-0.0310
Medium	805	0.897	0.464	0.496	0.0580	-0.0465
Large	655	0.759	0.410	0.603	0.0276	-0.0620
Small – Large		0.149	0.068	-0.181	0.0397	0.0310
(t-statistic)		(5.39)	(3.95)	(-5.35)	(2.48)	(2.02)
Panel E: Fund Expense Ratio Categories						
High	1028	0.979	0.512	0.491	0.0879	-0.0552
Medium	838	0.839	0.425	0.520	0.0394	-0.0596
Low	856	0.730	0.380	0.495	0.0228	-0.0455
High – Low		0.249	0.131	-0.004	0.0650	-0.0097
(t-statistic)		(7.79)	(6.68)	(-0.14)	(3.54)	(-0.53)

Table 4: 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
Small	1.00		
Mid	0.65	1.00	
Large	0.59	0.54	1.00

Stock Value-Growth	G	B	V
Growth	1.00		
Blend	0.72	1.00	
Value	0.60	0.82	1.00

Fund Size	S	M	L
Small	1.00		
Medium	0.54	1.00	
Large	0.52	0.44	1.00

Fund Expense Ratio	L	M	H
Low	1.00		
Medium	0.68	1.00	
High	0.61	0.48	1.00

Table 5: 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)
$AvgTurn$	0.651	0.120	0.473	0.162	0.186	0.401
	(8.65)	(0.98)	(3.08)	(1.48)	(1.91)	(5.09)
$AvgTurn\_Stock\_Size$		0.535				
		(5.27)				
$AvgTurn\_Stock\_VG$			0.180			
			(1.28)			
$AvgTurn\_Fund\_Size$				0.527		
				(6.03)		
$AvgTurn\_Fund\_Exp$					0.487	
					(7.01)	
$AvgTurnSim$						0.284
						(7.35)
Observations	303,933	271,888	271,888	303,564	285,897	263,645
Within-fund R^2 (%)	1.28	1.83	1.38	1.81	1.84	2.27

Table 6: 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)
$Sentiment_t$	0.0361			0.0238	0.0531			0.0487
	(3.35)			(2.98)	(3.17)			(4.65)
$Volatility_t$		0.746		0.538		0.938		0.809
		(7.78)		(5.58)		(7.23)		(7.98)
$Liquidity_t$			-0.193	-0.0889			-0.212	-0.138
			(-4.55)	(-3.96)			(-4.14)	(-4.58)
$Business\ Cycle_t$				-0.0127				-0.00334
				(-1.99)				(-0.66)
$Market\ Return_t$				-0.0342				0.0171
				(-1.26)				(0.34)
$Time\ Trend_t$	0.0000	-0.0001	-0.0001	-0.0001	0.0006	0.0004	0.0005	0.0005
	(0.06)	(-0.57)	(-0.81)	(-0.47)	(5.21)	(3.88)	(3.44)	(5.20)
R^2	0.002	0.007	0.001	0.010	0.524	0.541	0.377	0.677
$R^2 - R^2$(trend only)	0.002	0.007	0.001	0.010	0.171	0.188	0.024	0.324
Observations	267,025	275,543	275,543	267,025	372	382	382	372

Table 7: Relation Between Fund Performance and Average Turnover

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

	(1)	(2)	(3)	(4)	(5)	(6)
$AvgTurn_{i,t-1}$	0.00784			0.00785		0.00575
	(2.25)			(2.20)		(1.48)
$AvgTurnSim_{i,t-1}$		0.00327			0.00306	0.00195
		(3.69)			(3.26)	(2.50)
$FundTurn_{i,t-1}$			0.00123	0.00107	0.00127	0.00121
			(6.63)	(6.53)	(7.37)	(7.39)
Observations	310,908	286,738	285,897	285,897	263,645	263,645

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