

Do Funds Make More When They Trade More?

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Abstract

We find that active mutual funds perform better after trading more. This time-series relation between a fund's turnover and its subsequent benchmark-adjusted return is especially strong for small, high-fee funds. These results are consistent with high-fee funds having greater skill to identify time-varying profit opportunities and with small funds being more able to exploit those opportunities. In addition to this novel evidence of managerial skill and fund-level decreasing returns to scale, we find evidence of industry-level decreasing returns: The positive turnover-performance relation weakens when funds act more in concert. We also identify a common component of fund trading that is correlated with mispricing proxies and 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 find that funds do earn more after trading more heavily. Specifically, 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.

The turnover-performance relation is stronger for funds that charge higher fees as well as funds that are smaller in size. These results further support the presence of skill and provide novel evidence of decreasing returns to scale at the individual-fund level. Because smaller funds trade smaller amounts, decreasing returns to scale associated with liquidity costs allow smaller funds to better exploit time-varying profit opportunities. Identifying those opportunities requires skill, and managers with greater skill should earn higher fees. Our results suggest that higher-fee funds are more skilled at identifying time-varying profit opportunities, and that smaller funds can better exploit those opportunities. Small, high-fee funds also have especially volatile turnover, consistent with their having greater abilities to identify and exploit time-varying opportunities.

Fund trading has a common component that 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.

These perceptions seem justified, because average turnover positively predicts a fund's

¹As 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).

future return, even when we control for the fund’s own turnover. This predictive relation is highly significant: a one-standard-deviation increase in average turnover is associated with a 0.80% per year increase in fund performance. A fund’s performance can thus be predicted not only by its own turnover but also by other funds’ turnover. More trading by other funds appears to indicate 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.

The positive relation between average turnover and future fund returns is weaker in periods when funds act more in concert, as measured by the average correlation among the funds’ benchmark-adjusted returns. This evidence is consistent with decreasing returns to scale at the level of the active-management industry (see Pástor and Stambaugh, 2012, and Pástor, Stambaugh, and Taylor, 2014). When funds act in concert, pursuing the same profit opportunities, prices move and those opportunities become harder to find.

The relation between a fund’s return and lagged average turnover becomes even stronger when the average is calculated only across funds in the same size-fee category as the given fund. The turnover of other same-category funds thus seems to be a better signal of the fund’s profit opportunities than the turnover of different-category funds. This result suggests that funds in different size-fee categories pursue somewhat different opportunities.

We provide an investment perspective on the turnover-performance relation by applying a novel mapping between time-series regressions and investment strategies. We show that the estimated slope coefficient from our regression of a fund’s return on its lagged turnover is closely related to the average return of a strategy that dynamically allocates between the fund and its benchmark. The strategy invests more in the fund following higher turnover by the fund. When implemented for all funds and combined with a short position in the strategy’s static counterpart, this “timing” strategy produces an impressive annual Sharpe ratio of 0.79, which exceeds the Sharpe ratios of the market, size, value, and momentum factors over the same 1979–2011 period. This finding provides an additional perspective on the economic significance of the turnover-performance relation identified by our study.

Finally, we consider a cross-sectional investment strategy that captures an element of the time-series relation between turnover and performance. Every month, we sort funds into portfolios based on the ratio of a fund’s recent turnover to the trailing historical average of that fund’s turnover. We find that funds whose turnover is high based on this ratio tend to outperform funds whose turnover is low. Funds that have recently traded more than usual perform especially well when there are better profit opportunities in the market, as

judged by high sentiment. This strategy’s performance is statistically significant, but it is weaker than the performance of the timing strategy, which is more directly motivated by our turnover-performance relation.

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 investigation of skill adds a new dimension to the literature on the relation between mutual fund turnover and fund performance. The empirical evidence on this relation is mixed. For example, Elton, Gruber, Das, and Hlavka (1993) and Carhart (1997) find a negative turnover-performance relation, Wermers (2000) 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. The main difference between these studies and ours is that all of these studies examine the cross-sectional relation between turnover and performance, whereas we focus on the time-series relation.⁴

We obtain our time-series results from panel regressions of fund returns on lagged fund turnover and various controls, including fund fixed effects. Fund fixed effects are crucial for finding a positive turnover-performance relation. With fund fixed effects, identification comes from within-fund time variation in turnover and performance, not from the cross-sectional variation exploited in the prior studies mentioned above. If we drop fund fixed effects, the positive turnover-performance relation weakens to marginally significant. The relation wanes further if we replace fund fixed effects with month fixed effects, thereby isolating pure cross-sectional variation. These results underline the time-series nature of the turnover-performance relation. We do not find that higher-turnover funds perform better; we find that a given fund performs better when it trades more.

To help interpret our results from panel regressions with fixed effects, we present a formula for the slope coefficient from such regressions estimated in an unbalanced panel. The slope

²See, 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.

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

⁴The two studies that find a positive relation differ from our study in other ways as well. Dahlquist, Engström and Söderlind find this positive relation in a small sample of Swedish mutual funds (80 funds in 1993–1997); our sample of U.S. funds is much larger. Chen, Jagadeesh and Wermers find this relation based on the returns of the funds’ disclosed stock holdings, whereas we analyze the returns of the funds themselves.

from a panel regression with fund fixed effects is a weighted average of the slopes estimated fund by fund in pure time-series regressions of return on turnover. Greater weight is given to funds with longer samples and more volatile turnover. Analogously, with month fixed effects, the panel regression slope is a weighted average of the month-by-month estimates in pure cross-sectional regressions of return on turnover. More generally, our formula also clarifies the relation between a panel regression slope and the well-known estimator of Fama and MacBeth (1973). The Fama-MacBeth estimator emerges as a special case from a panel regression with month fixed effects if the panel is balanced and the cross-sectional variance of the independent variable is constant over time.

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 (2014) 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 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, 2013, 2014), 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, Litov, Wachter, and Wurgler (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. 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. Lan and Wermers (2014) relate fund and stock performance to funds’ investment horizons. 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 (2010) 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 seems novel.

The rest of the paper is organized as follows. Section 2 documents the basic turnover-performance relation. Section 3 examines this relation across categories of funds based on size and fees. Section 4 analyzes the common component of turnover and its predictive power for fund returns. Section 5 provides two investment perspectives on the turnover-performance relation. Section 6 concludes.

2. The Turnover-Performance Relation

Active mutual funds pursue alpha—returns in excess of their benchmarks. The funds’ managers perceive opportunities for producing alpha and trade to exploit them. A manager trades more when he identifies more alpha-producing opportunities, so a skilled manager should perform better after he trades more. We look for such evidence of skill by estimating the relation between a fund’s turnover and its subsequent return. We specify this turnover-performance relation for a given fund i as the linear regression

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

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 $t - 1$. A positive b_i is consistent with skill.⁵

⁵In 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,

The skill we investigate is an ability to exploit opportunities in period $t - 1$ for which a nontrivial fraction of the payoff occurs in period t . A prime example is a purchase of an underpriced security in period $t - 1$ followed by the correction of the mispricing in period t . One can imagine other forms of skill 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 the same period in which the fund trades to exploit those opportunities. Such skill would impart no time-series relation between turnover in period $t - 1$ and performance in period t . Similarly, the turnover-performance relation would be very weak, possibly undetectable, for a fund skilled only in identifying long-horizon opportunities that deliver most of their payoffs after the next period. Moreover, detecting skill using the turnover-performance relation requires variation over time in the extent to which profitable opportunities arise. In principle, a fund could be skilled at identifying opportunities that arise to the same extent every period. Such skill would impart no variation over time in trading and expected payoffs. Although the turnover-performance relation 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 (2014), 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. We use gross rather than net returns because our goal is to measure a fund’s ability to outperform a benchmark, not the value delivered to clients after fees. We estimate all regressions at a monthly frequency, but a fund’s turnover is reported only as the total for its fiscal year. Thus, we measure turnover, $X_{i,t-1}$, by the variable $FundTurn_{i,t-1}$, which is the fund’s turnover for the most recent 12-month period that ends before month t . This measure, reported by CRSP, is defined by the SEC as the lesser of the fund’s total purchases and sales, divided by the fund’s 12-month average total net asset value. By largely excluding turnover arising from flows to and from the fund, this measure reflects portfolio decisions to replace some holdings with others. We winsorize $FundTurn_{i,t-1}$ at the 1st and 99th percentiles.

To increase the power of our inferences in equation (1), we estimate a pooled time-series

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 (1).

and cross-sectional regression that imposes the restriction

$$b_1 = b_2 = \dots = b , \quad (2)$$

either across all funds or across funds within size-fee categories discussed later. 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 (1) when the restriction in (2) is imposed across all funds. When later allowing b to differ across size-fee categories, we also include fixed effects for those categories, in which case a fund's a_i equals the sum of its fund and category fixed effects. The regression specification combining equations (1) and (2), which isolates the time-series contribution of turnover to performance, is our main specification. For comparison, we also consider other specifications, as we explain next.

2.1. Time-series versus cross-sectional variation

Table 1 reports the estimated slope coefficient on turnover, or \hat{b} , for various specifications of the panel regression capturing the turnover-performance relation. The top left cell reports \hat{b} for the most parsimonious specification, which imposes not only the restriction (2) but also

$$a_1 = a_2 = \dots = a . \quad (3)$$

By removing fund fixed effects from our main specification, this additional restriction brings cross-sectional variation into play when estimating b . The estimate \hat{b} in the top 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 top right cell of Table 1 reports \hat{b} from a purely cross-sectional specification, in which fund fixed effects a_i are replaced by month fixed effects a_t . That is, we estimate the model

$$R_{i,t} = a_t + bX_{i,t-1} + \epsilon_{i,t} . \quad (4)$$

Given the month fixed effects, the OLS estimate \hat{b} from this panel regression reflects only cross-sectional variation in turnover and performance. This statement emerges clearly from the fact that \hat{b} is equal to a weighted average of the slope estimates from pure cross-sectional regressions of performance on turnover. Specifically, let \hat{b}_t denote the slope from the cross-sectional regression of $R_{i,t}$ on $X_{i,t-1}$ estimated at time t . We prove in the appendix (see Proposition A1) that \hat{b} from equation (4) obeys the relation

$$\hat{b} = \sum_{t=1}^T w_t \hat{b}_t , \quad (5)$$

where the weights w_t are given by

$$w_t = \frac{N_t \hat{\sigma}_{x_t}^2}{\sum_{s=1}^T N_s \hat{\sigma}_{x_s}^2} , \quad (6)$$

N_t is the number of observations at time t , and $\hat{\sigma}_{x_t}^2$ is the sample variance of $X_{i,t-1}$ across i . This weighting scheme places larger weights on cross-sectional estimates from periods with more observations and periods in which the independent variable exhibits more cross-sectional variance. The relation in equation (5) 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 \hat{b}_t . The Fama-MacBeth estimator is a special case of equation (5) 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., $\hat{\sigma}_{x_t}^2 = \hat{\sigma}_x^2$ for all t).

The estimate \hat{b} in the top right cell of Table 1, 0.00030, is positive but statistically insignificant ($t = 1.61$). The point estimate is smaller than in the top left cell, which shows that isolating cross-sectional variation weakens the turnover-performance relation. There is no significant cross-sectional relation between turnover and performance.

The bottom left cell of Table 1 reports \hat{b} from our main specification, which combines equations (1) and (2):

$$R_{i,t} = a_i + bX_{i,t-1} + \epsilon_{i,t} . \quad (7)$$

Given the fund fixed effects, the OLS estimate \hat{b} from this panel regression reflects only time-series variation in turnover and performance. In symmetry with our earlier discussion, \hat{b} is a weighted average of the slope estimates from pure time-series regressions. Specifically, let \hat{b}_i denote the estimated slope from the time-series regression in equation (1). Then \hat{b} from equation (7) is given by

$$\hat{b} = \sum_{i=1}^N w_i \hat{b}_i , \quad (8)$$

where the weights w_i are given by

$$w_i = \frac{T_i \hat{\sigma}_{x_i}^2}{\sum_{n=1}^N T_n \hat{\sigma}_{x_n}^2} , \quad (9)$$

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

The estimate \hat{b} in the bottom 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 result of this 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%. Another way of judging the economic significance of the turnover-performance relation appears later in Section 5. In that section, we prove that \hat{b} in the bottom left cell of Table 1 is proportional to the average return of an investment strategy that involves dynamic reallocation between active funds and their passive benchmarks.

Finally, the bottom right cell of Table 1 reports \hat{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 bottom left cell, and it is similarly significant ($t = 6.77$). The only difference from the bottom 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. Overall, Table 1 clearly shows that it is the presence of fund fixed effects, not month fixed effects, that is crucial to detecting a positive turnover-performance relation. The relation thus seems to be of a time-series as opposed to cross-sectional nature.

Why is the cross-sectional turnover-performance relation weaker than the time-series relation? One potential answer could be managerial overconfidence. If some fund managers are consistently overconfident in their trading abilities, they trade too much, incurring transaction costs without commensurately increasing performance. Such excessive trading can weaken the positive turnover-performance relation across funds. Consistent with this idea, Christoffersen and Sarkissian (2011) argue that overconfidence leads mutual fund managers to trade too much.⁶ Overconfidence is not incompatible with skill—managers can be skilled at recognizing profit opportunities and at the same time wrong in gauging how much skill they have. In similar spirit, a basketball player may be a skilled shooter and at the same time shoot too much at the expense of his win-loss record. Overconfidence can thus in principle induce even a negative cross-sectional turnover-performance relation. That relation opposes any skill-driven positive relation, unless the cross-sectional relation is removed by including

⁶Christoffersen 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.

fund fixed effects.

2.2. 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 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.⁷ 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 bottom 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.

We estimate the turnover-performance relation at the monthly frequency. Even though funds report their turnover only annually, most of the variables used in our subsequent analysis, such as fund returns, fund size, industry size, sentiment, volatility, liquidity, correlation, 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

⁷Gormley 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.

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 fund turnover 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 fund turnover. We find that the interaction term does not enter significantly, suggesting that our constant-slope specification is appropriate.

The positive turnover-performance relation emerges not only from the panel regression in Table 1, which imposes the restriction (2), but also from fund-by-fund regressions. For each fund i , we estimate the slope coefficient b_i from the time-series regression in equation (1) in the full sample. We find that 61% of the OLS slope estimates \hat{b}_i are positive. Moreover, 9% (4%) of the \hat{b}_i 's are significantly positive at the 5% (1%) confidence level. A weighted average of these \hat{b}_i 's appears in the bottom left cell of Table 1, as shown in equation (8).

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.⁸ Moreover, the contribution of IPO allocations to fund performance seems modest. For each year between 1980 and 2013, we calculate the ratio of total money left on the table across all IPOs, obtained from Jay Ritter's website, to total assets of active domestic equity mutual funds, obtained from the Investment Company Institute. This ratio, whose mean is 0.30%, exceeds the contribution of IPO allocations to fund performance because mutual funds receive only about 25% to 41% of IPO allocations, on average.⁹ 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 bottom row of Table 1 remain positive and significant, with t -statistics in excess of 3.2.

⁸See, for example, Nimalendran, Ritter, and Zhang (2007) and Goldstein, Irvine, and Puckett (2011).

⁹These estimates are from Reuter (2006), Ritter and Zhang (2007), and Field and Lowry (2009).

We benchmark each fund’s performance against the index selected for each fund category by Morningstar. For example, for small-cap value funds, the benchmark is the Russell 2000 Value Index. Such an index-based adjustment 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. 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 very similar results when we adjust fund returns by using the three Fama-French factors or the four factors that also include momentum. In both cases, the slope coefficients in the top row of Table 1 remain insignificant while the slopes in the bottom row continue to be highly significant, with t -statistics ranging from 7.14 to 8.76.

We assess fund performance by subtracting the 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 top row are insignificant while the slopes in the bottom row are highly significant, with t -statistics of about 7.6.

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.¹⁰ The second change, identified by Pástor, Stambaugh, and Taylor (2014), 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

¹⁰In 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*.

significant, with t -statistics of 4.37 and 3.74 in the bottom row. In the online appendix, we report the counterparts of all of our tables estimated in the 2000–2011 subperiod.

3. Fund Size and Fees Matter

Our evidence so far reveals that the typical fund performs better after it trades more. Next, we ask whether this turnover-performance relation differs across funds. We focus on two readily observed fund characteristics, a fund’s size and its expense ratio (or “fee,” for short). Both characteristics are related to fund performance. Fund size matters because larger funds tend to trade larger amounts. In the presence of decreasing returns to scale associated with liquidity costs, larger funds are less able to exploit alpha-producing opportunities (e.g., Perold and Salomon, 1991). Identifying those opportunities requires skill, and managers with greater skill should receive greater fee revenue in equilibrium (e.g., Berk and Green, 2004). Among funds of similar size, a manager with greater skill should thus have a higher expense ratio.

We explore the roles of fund size and fees in the turnover-performance relation. For each month t , we compute the terciles of $FundSize_{i,t-1}$ and $ExpenseRatio_{i,t-1}$, the most recent values of size and fees available from CRSP prior to month t . Each fund in the sample in month t is assigned to one of the resulting size and fee categories. We then estimate the turnover-performance relation, first separately within each of the size and fee categories and then within each of the nine size-fee categories for the 3×3 classification. To do so, we add fixed effects for the categories to the previous specification containing fund fixed effects. We estimate separate slopes on $FundTurn_{i,t-1}$ for each category, thereby imposing the restriction in equation (2) only within a category.

Table 2 reports the estimated slope coefficients on turnover. We see that both fund size and fees matter in the turnover-performance relation: the turnover coefficient is decreasing in fund size and increasing in expense ratio. The role of fund size is dramatic. In the one-way sort, small funds have a turnover coefficient of 0.00186 (t -statistic: 7.56), whereas medium-sized funds have a coefficient not even half as big, equal to 0.00086 ($t = 3.74$). The coefficient for large funds is lower by another half and insignificant—only 0.00043 ($t = 1.46$). Fees also play a strong role, even though the turnover-performance relation is significantly positive in all fee categories. In the one-way sort, the turnover coefficients increase monotonically in fees, producing a significant high-low difference ($t = 4.06$) and a high-fee coefficient three times higher than the low-fee value (0.00170 versus 0.00058).

The results in Table 2 for the 3×3 two-way sort are consistent with the effects of size and fees discussed above. For a given level of one characteristic, the other characteristic matters in the same direction as in the one-way sort results, judging by the signs of the small-large (size) and high-low (fee) differences. The joint roles of size and fees also imply a larger turnover coefficient for small, high-fee funds than for large, low-fee funds. That difference is indeed positive, with a t -statistic of 3.55. Small, high-fee funds have the largest t -statistic and the second largest slope coefficient among the nine fund categories.

The strong turnover-performance relation for small, high-fee funds has especially large economic significance because turnover is most volatile for those funds. Table 3 reports summary statistics for turnover within the size and fee categories. Panel B shows that $FundTurn_{i,t-1}$ for small, high-fee funds has a standard deviation of 0.547, as compared to 0.438 for all funds and only 0.379 for large, low-fee funds. In general, turnover volatility is increasing in fees and decreasing in fund size. Suppose we translate a one-standard-deviation difference in turnover to a difference in subsequent return. This measure of economic significance is especially large for small, high-fee funds, because their turnover has not only a large slope but also high volatility. Combining these values from Tables 2 and 3 implies that a one-standard-deviation increase in turnover for small, high-fee funds translates to an increase in expected return of 1.25% per year ($= 0.00191 \times 0.547 \times 1200$). This is a large effect, both relative to other funds and in absolute terms. Relative to other funds, the corresponding value for large, low-fee funds is only 0.21% ($= 0.00046 \times 0.379 \times 1200$), and the value for all funds, reported earlier, is 0.65%. In absolute terms, the 1.25% expected return increase is comparable to the average $GrossR_{i,t}$ of small, high-fee funds, which is 0.0938% per month, or 1.13% per year, as shown in Table 4. Interestingly, Table 4 also shows that smaller funds outperform larger funds, and high-fee funds outperform low-fee funds, in gross returns (though not in net returns). These patterns are similar to those in Table 2, suggesting that the turnover-performance relation might play a role in overall fund performance.

The importance of fund size in the turnover-performance relation in Table 2 presents novel evidence of decreasing returns to scale at the fund level. Prior studies of fund-level decreasing returns generally look for a direct negative relation between a fund's return and its size.¹¹ While point estimates from such approaches are often consistent with decreasing returns, statistical significance is elusive when applying methods that avoid econometric biases (see Pástor, Stambaugh, and Taylor, 2014). The disadvantage of a fund's being large instead emerges here as a weaker relation, or even no relation, between the fund's trading and its subsequent performance, in sharp contrast to the strong positive relation for small funds.

¹¹See, for example, Chen, Hong, Huang, and Kubik (2004), Yan (2008), and Reuter and Zitzewitz (2013).

Unlike the directly estimated relation between fund size and return, the role of fund size in the turnover-performance relation is highly significant, both economically and statistically.

More trading should produce higher returns the greater is the manager’s skill in identifying profitable opportunities. Managers with more skill should receive more fee revenue, as noted earlier. Fee revenue is proportional to the expense ratio for a given fund size, implying a positive partial correlation between skill and expense ratio, conditional on size. Recall from the results of the two-way sort that within each size category, the turnover-performance relation is stronger for high-fee funds, consistent with such funds having greater skill. A one-way sort similarly reveals a stronger relation for high-fee funds, consistent with a positive simple correlation between skill and expense ratio. The latter correlation does not necessarily follow, as it 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.

Besides fees, we consider two additional proxies for fund skill. First, we calculate gross alpha adjusted for both fund-level and industry-level returns to scale, following Pástor, Stambaugh, and Taylor (2014). Second, we take the unadjusted gross alpha over the fund’s lifetime. 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 additional robustness results. For example, all the conclusions from Table 2 continue to hold if we replace benchmark-adjusted fund returns by returns adjusted for the three Fama-French factors or the four factors that also include momentum. In addition, while the regressions in Table 2 exclude month fixed effects, including such fixed effects produces very similar results, and so does including benchmark-month fixed effects. Overall, our results suggest that high-fee funds have greater skill in identifying time-varying profit opportunities, and small funds are more able to exploit those opportunities.

Small funds also have higher average turnover than large funds. This result, shown in Panel A of Table 3, is consistent with a natural skill-based sorting of managers. Some managers are more skilled at identifying short-lived opportunities yielding profits over short horizons, while others are more adept at identifying opportunities with longer holding periods that allow patient trading. In a competitive market for managerial talent, one would expect the short-horizon managers to manage small funds: the liquidity constraints that bite when trades must be done quickly render their talents less useful in trading large amounts. In contrast, one would expect the long-horizon managers to manage large funds: their skills can be more profitably exploited by trading larger amounts, since their trades can be executed more patiently. Therefore, this sorting mechanism implies that smaller funds should hold

their positions over shorter periods. This implication is supported by Panel A of Table 3, because the higher average turnover of smaller funds suggests those funds have shorter holding periods. The sorting mechanism also implies that larger funds should have more persistent turnover due to more patient trading. Indeed, Panel C of Table 3 shows that turnover of larger funds exhibits higher autocorrelation.

4. What Other Funds Do Matters

We have shown that if Fund ABC trades more than usual this period, the fund typically performs better than usual next period. Suppose now that many other funds trade more than usual this period. Are there implications for the performance of Fund ABC? On the one hand, this heavier trading by other funds could be good news for Fund ABC. If there is more mispricing this period, as indicated by many funds trading more, then any opportunities identified by Fund ABC could be more profitable. On the other hand, if the other funds are identifying the same opportunities and thus acting in concert, their heavier trading could produce especially large price impacts, reducing mispricing that would otherwise benefit Fund ABC. This section considers both of these potential effects in exploring whether the turnover-performance relation depends on the trading activity of other funds. We begin by considering a mispricing-based explanation for common variation in fund turnover. We then investigate how that common variation impacts the turnover-performance relation.

4.1. Mispricing and Trading

When do funds, viewed collectively, trade more than usual? If alpha-producing opportunities arise from mispricing, then periods with more mispricing should be those when funds trade more. A simple measure of the common component in fund trading is the cross-sectional average of individual fund turnover. We let $AvgTurn_t$ denote average turnover contemporaneous with month t , that is, the average turnover across funds' 12-month fiscal periods that contain month t . $AvgTurn_t$, plotted in Panel A of Figure 1, fluctuates between 59% and 102% per year from 1979 to 2011.¹² This series has a 95% correlation with the first principal component of individual fund turnover. We ask whether $AvgTurn_t$ is higher when mispricing is more likely. We use three proxies for the likelihood of mispricing: $Sentiment_t$,

¹²CRSP turnover data are missing in 1991 for unknown reasons. We therefore treat $AvgTurn$ as missing in 1991 in our regressions. In Figure 1, 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.

$Volatility_t$, and $Liquidity_t$. The three series are plotted in Panel B of Figure 1.

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, a regression of $AvgTurn_t$ on $Sentiment_t$ produces a significantly positive coefficient ($t = 3.17$), as shown in the first column of Table 5. We include a time trend in the regression, given the positive trend in $AvgTurn_t$ evident in Figure 1. As reported in the last row, the R^2 in the regression including $Sentiment_t$ exceeds the R^2 when regressing on just the time trend by 0.171.

The second mispricing proxy, $Volatility_t$, is the cross-sectional standard deviation in month t of the returns on individual U.S. stocks.¹³ The rationale for this variable is that higher volatility corresponds to greater uncertainty about future values and thus greater potential for investors to err in assessing those values. As a result, periods of high volatility admit greater potential mispricing, and we expect funds exploiting such mispricing to trade more when volatility is high. Consistent with this prediction, a regression of $AvgTurn_t$ on $Volatility_t$ produces a significantly positive coefficient ($t = 7.23$), as shown in column 2 of Table 5. The R^2 in that regression, which again includes a time trend, exceeds the R^2 in the trend-only regression by 0.189.

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 $AvgTurn_t$ on $Liquidity_t$ yields a significantly negative coefficient ($t = -4.14$), reported in column 3 of Table 5. Including $Liquidity_t$ increases the R^2 versus the trend-only regression by 0.024, a more modest increase than produced by 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. This all-inclusive regression, reported in column 4 of Table 5, also adds two additional variables that

¹³We thank Bryan Kelly for providing this series.

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 0.324.¹⁴ Overall, the results make sense: funds trade more when there is more mispricing.

What mispricing are funds exploiting? To see whether funds trade based on well-known market anomalies, we regress the returns of eleven such anomalies, as well as their composite return, on lagged average fund turnover. The eleven anomalies, whose returns we obtain from Stambaugh, Yu, and Yuan (2012), involve sorting stocks based on two measures of financial distress, two measures of stock issuance, accruals, net operating assets, momentum, gross profitability, asset growth, return on assets, and the investment-to-assets ratio. We find no significant slopes on average turnover. To the extent that funds trade more when there is more mispricing, they must be 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 Table 5, 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 any of our inferences in Table 5.

4.2. Other Funds: Evidence That They Matter

Next, we investigate how the trading of other funds enters the turnover-performance relation. We first ask whether average lagged fund turnover, which reflects commonality in fund trading, helps predict a given fund's subsequent performance. We denote average lagged

¹⁴If we exclude the time trend from the regressions, we find results similar to those reported in Table 5. *Volatility* and *Liquidity* continue to enter significantly with the same signs as in Table 5, 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. This evidence suggests that *Sentiment* is better at capturing deviations of $AvgTurn$ from its trend than in capturing the raw variation in $AvgTurn$.

fund turnover, or the average of $FundTurn_{i,t-1}$ across i , by $AvgTurn_{t-1}$.¹⁵ The first column of Table 6 reports the result of replacing $FundTurn_{i,t-1}$ by $AvgTurn_{t-1}$ and then repeating the regression from the bottom left cell of Table 1, which includes fund fixed effects.¹⁶ We see a significantly positive coefficient on $AvgTurn_{t-1}$ ($t = 2.13$), indicating that the common component of fund trading helps predict individual fund performance. The estimated slope coefficient, 0.00741, implies substantial economic significance. Given the time-series standard deviation of $AvgTurn_{t-1}$, 0.090, a one-standard-deviation increase in the variable translates to an increase in expected return of 0.80% per year ($= 0.00741 \times 0.090 \times 1200$).

The information in $AvgTurn_{t-1}$ about a fund’s subsequent performance is undiminished by conditioning on the fund’s own turnover. The results in column 2 of Table 6 reveal that the coefficient and t -statistic for $AvgTurn_{t-1}$ are little changed by controlling for $FundTurn_{i,t-1}$. The importance of either variable is insensitive to whether the other is included, because the average correlation between $FundTurn_{i,t-1}$ and $AvgTurn_{t-1}$ is a modest 0.131 (the “all-all” value in Panel A of Table 7). Both turnover variables remain significant also after controlling for additional variables described below (columns 3 through 7 of Table 6).

A simple story emerges from the joint abilities of $FundTurn_{i,t-1}$ and $AvgTurn_{t-1}$ to predict fund performance. A given fund’s turnover, $FundTurn_{i,t-1}$, is higher—and its subsequent performance is better—when its own manager identifies more alpha-producing 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.

Heavier trading by other funds is not necessarily all good news, however. Other funds are competitors whose trades can move prices. A stronger presence of active managers in the stock market produces greater price corrections and thus lowers the active managers’ alphas. That is the idea behind the concept of industry-level decreasing returns to scale, introduced by Pástor and Stambaugh (2012). In line with that concept, Pástor, Stambaugh,

¹⁵Note 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 4.1, 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 4.1 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 4.1 to emphasize the contemporaneous nature of the analysis in that section. We hope the reader will pardon this slight abuse of notation.

¹⁶Month fixed effects must be omitted because a common time series is used as a regressor for each fund. Also, the regressions in Table 6 exclude a time trend, but the results are very similar if we include one.

and Taylor (2014) find empirically that fund performance is negatively related to the size of the active management industry. Following that study, we define $IndustrySize_{t-1}$ as the value in month $t - 1$ of the total assets managed by all funds in our sample, divided by the total market value of U.S. stocks. Our evidence, shown in column 3 of Table 6, confirms a significantly negative relation between fund performance and $IndustrySize_{t-1}$.

Industry size is one way of measuring the degree of competition among funds. Another way, which we introduce here, is to gauge the extent to which funds act in concert. We use a simple return-based measure, $AvgCorr_{t-1}$, which is the average pairwise correlation between all individual funds' benchmark-adjusted gross returns in the 12 months ending in month $t - 1$. $AvgCorr_{t-1}$ fluctuates between 0.01 and 0.26 from 1979 to 2011. We interpret higher values of $AvgCorr_{t-1}$ as indicating more concerted active trading by funds. We find that $AvgCorr_{t-1}$ is negatively related to fund performance ($t = -2.42$; see column 4 of Table 6). This result is consistent with the interpretation that when funds trade more in concert, prices are impacted and profit opportunities are reduced.

The price impact of funds' concerted trading should be stronger when those funds trade more heavily. Therefore, when $AvgTurn_{t-1}$ is higher, the effect of $AvgCorr_{t-1}$ on performance should be less favorable. Similarly, the more funds act in concert (i.e., the higher $AvgCorr_{t-1}$), the less favorable should be their heavier trading ($AvgTurn_{t-1}$). Either way, we expect fund performance to be negatively related to the interaction term $AvgTurn_{t-1} \times AvgCorr_{t-1}$. This is indeed the case, as shown in column 5 of Table 6 ($t = -2.69$). At the same time, the slope on $AvgTurn_{t-1}$ remains positive and significant. We thus see simultaneous support for both the positive and negative aspects of heavier trading by other funds. This evidence suggests that the benefit of the greater mispricing reflected in other funds' heavier trading is countered by greater price correction when those funds act more in concert.

This opposing effect of funds acting in concert is consistent with the previously discussed concept of industry-level decreasing returns to scale. The underlying mechanism behind that concept is that a larger industry implies more money chasing the same alpha-producing opportunities, thereby moving prices more and reducing each active fund's alpha. Our measure of $AvgTurn_{t-1} \times AvgCorr_{t-1}$ directly addresses this effect of more money acting in concert. The significantly negative relation between this term and performance provides additional and novel evidence of industry-level decreasing returns to scale.

Interestingly, adding the interaction term in column 5 of Table 6 changes the sign of the slope on $AvgCorr_{t-1}$ from negative to positive ($t = 2.55$). This result highlights a positive

aspect of concerted fund trading, as measured by $AvgCorr_{t-1}$. If funds choose to make similar trades at the same time, they must perceive those trades as attractive. If those funds are skilled, their perceptions are correct and their concerted trading thus indicates more mispricing, with favorable implications for performance. This positive effect of concerted trading is opposed by the negative effect discussed earlier. Which effect prevails depends on the amount of other funds' trading. The estimates in column 5 indicate that when fund trading is light (i.e., $AvgTurn_{t-1}$ is low), the positive effect prevails and $AvgCorr_{t-1}$ is positively related to performance. When trading is heavy, though, the negative effect prevails. The negative effect also prevails on average, as shown in column 4. We thus see that the benefit of the greater mispricing signaled by other funds' concerted trading is more than offset by the cost of greater price correction when those funds trade more heavily.

To explore the robustness of our inferences about how performance relates to what other funds do, we add the three mispricing proxies to the regression in Table 6 (column 6). We also allow $FundTurn_{i,t-1}$ to enter differently across the nine size-fee categories, as in Section 3 (column 7). In both specifications, the statistical significance of $AvgTurn_{t-1}$, $AvgCorr_{t-1}$, and their interaction is unaffected by the inclusion of the mispricing proxies, and the corresponding slope coefficients are close to those reported earlier. The three mispricing proxies enter with the same signs in predicting performance (Table 6) as they do in explaining the variation in $AvgTurn_{t-1}$ (Table 5), though in Table 6 only $Sentiment_{t-1}$ is significant ($t = 3.42$). This result suggests that turnover, with both its common and fund-specific dimensions, largely subsumes performance-relevant mispricing information in the other two mispricing proxies, $Volatility_{t-1}$ and $Liquidity_{t-1}$. In contrast, $Sentiment_{t-1}$ contains additional information about future fund performance.

So far we have treated other funds as being *all* other funds, for simplicity. For a given fund, "other" funds can also be defined more narrowly as those sharing the fund's characteristics. Motivation for this alternative definition arises from Table 7. Panel A reports the correlation between $FundTurn_{i,t-1}$ and $AvgTurn_{t-1}$, with the correlation averaged across all funds as well as across just the funds within a size and fee category. Panel B repeats the same calculations while replacing $AvgTurn_{t-1}$ with $OwnCellAvgTurn_{t-1}$, the average lagged turnover calculated across only those funds belonging to the same size and fee tercile as fund i in month t . When comparing Panels A and B, we see that $FundTurn_{i,t-1}$ has a lower average correlation with $AvgTurn_{t-1}$ than it has with $OwnCellAvgTurn_{t-1}$. This inequality holds for every one of the six one-way and nine two-way size and fee categories. These results reveal greater common variation in turnover among funds with similar sizes and fees than among all funds taken together.

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 the above evidence that the turnover of one’s own fund typically comoves more with the turnover of funds that have similar size and fees. It is also consistent with the natural sorting mechanism discussed at the end of Section 3.

Since there is more commonality in turnover among similar funds, it is natural to ask whether similar funds’ trading helps explain performance. We run regressions similar to those in Table 6 but replace $AvgTurn_{t-1}$ with $OwnCellAvgTurn_{t-1}$. The results are in Table 8. We also add $AvgTurn_{t-1}$ as an independent variable, allowing a horse race between it and its own-cell counterpart. The latter wins, consistent with the greater relevance of what other *similar* funds do. The t -statistics for $OwnCellAvgTurn_{t-1}$, which range from 3.11 to 7.02, are uniformly higher than the corresponding t -statistics for $AvgTurn_{t-1}$ in Table 6. Moreover, $AvgTurn_{t-1}$ becomes insignificant, driven out by $OwnCellAvgTurn_{t-1}$. Finally, $AvgCorr_{t-1}$ plays a similar role as before: the interaction term $OwnCellAvgTurn_{t-1} \times AvgCorr_{t-1}$ enters significantly negatively ($t = -2.90$).

Overall, our results show that a fund’s performance is related not only to its own turnover but also to that of other funds, especially other similar funds. Heavier trading by other funds signals greater mispricing and is positively related to performance, but there is also an opposing negative relation to the extent that funds act in concert.

5. Investment Perspectives

In this section, we take an investment perspective to assess the economic significance of our regression results. We examine the performance of two investment strategies designed to exploit the turnover-performance relation.

5.1. A Timing Investment Strategy

The first investment strategy is a portfolio of pure timing strategies, one for each active fund. For any given fund, the timing strategy dynamically varies the allocation between the fund and its passive benchmark, investing more in the fund when the fund’s turnover is higher. Specifically, for any fund i and month t , the strategy invests

$$\omega_{i,t-1} = FundTurn_{i,t-1} \tag{10}$$

dollars in fund i and $1 - \omega_{i,t-1}$ dollars in fund i 's benchmark. This strategy's benchmark-adjusted gross return in month t is thus equal to $R_{i,t}^{(tim)} = \omega_{i,t-1}R_{i,t}$. Recall that $R_{i,t}$, also denoted by $GrossR_{i,t}$, is fund i 's benchmark-adjusted gross return in month t .

We also examine a related non-timing strategy that invests a constant $\bar{\omega}_i$ dollars in fund i each month, where $\bar{\omega}_i$ is the time-series average of $\omega_{i,t}$ for fund i . The non-timing strategy's benchmark-adjusted gross return in month t is given by $R_{i,t}^{(notim)} = \bar{\omega}_i R_{i,t}$. We are ultimately interested in the difference between $R_{i,t}^{(tim)}$ and $R_{i,t}^{(notim)}$, which is the return on a strategy that goes long the timing strategy and short the non-timing strategy:

$$R_{i,t}^{(dif)} = (\omega_{i,t-1} - \bar{\omega}_i) R_{i,t} . \quad (11)$$

Positive values of $R_{i,t}^{(dif)}$ indicate that turnover-based timing for fund i adds value.¹⁷

We construct portfolios of these fund-level timing strategies, allocating across the full sample of funds as well as across various subsamples. For a given sample of funds, our portfolio invests one dollar in each existing fund's timing strategy each month, splitting the dollar between the fund and the benchmark following equation (10). Like a venture capital fund, this portfolio strategy calls capital and distributes it to investors at discrete points in time, as needed. When a new fund appears in the sample, we immediately raise one dollar of new capital and invest it in that fund's timing strategy. When a fund drops out of the sample, we return the capital associated with that fund's strategy.

5.1.1. The Timing Strategy's Average Returns

Table 9 reports the average values of $R_{i,t}^{(dif)}$ from equation (11) for the full sample of funds as well as for subsamples given by the size-fee categories considered earlier. We compute the averages in two ways. In Panel A, we average all available $R_{i,t}^{(dif)}$ values, thus treating each fund/month as a separate observation. The result can be interpreted as the average return on the typical dollar invested, which is often referred to as a dollar-weighted average return in investment practice. In Panel B, we first average $R_{i,t}^{(dif)}$ across all funds i in month t , and then average those averages across months. The result is the usual time-weighted average return, or the average return in a typical month. All averages are computed over the period 1979–2011.

Panel A of Table 9 shows that the average of $R_{i,t}^{(dif)}$ across all fund/months, 0.0235% per

¹⁷The long-short investment strategy whose return is given in equation (11) is not feasible in practice, both because it involves shorting mutual funds and because it relies on the full-sample time-series average $\bar{\omega}_i$, which is not known in real time. Nonetheless, the strategy is useful for our purposes since its average return can be directly mapped into our regression results, as explained below.

month, is significantly positive ($t = 6.53$). This result, reported in the “all-all” cell, indicates that the long-short timing strategy is profitable. The average return is also significantly positive in all three size categories as well as all three fee categories, and it is significantly higher for funds that are smaller and funds that charge higher fees. The strategy works best for small, high-fee funds, earning 0.0541% per month. The results in Panel B are similar, except that the effect of fund size disappears. The average return in the all-all cell is 0.0257% per month ($t = 4.49$), even larger in magnitude than its counterpart in Panel A.

These average returns look deceptively small. Since the timing and non-timing strategies underlying $R_{i,t}^{(dif)}$ are highly correlated, the volatility of $R_{i,t}^{(dif)}$ is small as well. For example, the time-series volatility of the portfolio returns underlying the all-all cell in Panel B is only 0.1123% per month. If we scale the weights in equation (10) so that the strategy’s volatility is 20% per year, the all-all average return rises from 0.0257% per month to 1.32% per month, or 15.88% per year! Put differently, the strategy’s Sharpe ratio is 0.23 per month ($= 0.0257/0.1123$), or 0.79 per year. This impressive Sharpe ratio exceeds those of Carhart’s (1993) market, size, value, and momentum factors over the same 1979–2011 period (those ratios range from 0.20 for size to 0.51 for momentum).

5.1.2. The Equivalence Between Panel Regressions and Timing Strategies

Our timing strategy invests more in the fund when the fund trades more (equation (10)). The motivation for this strategy is our regression evidence in Tables 1 and 2. Our regressions identify a significantly positive turnover-performance relation, but only when we include fund fixed effects to isolate time-series variation within funds. Our timing strategy is designed to exploit this variation. This implementation of the turnover-performance relation is so fitting that there is a formal equivalence between our investment results and regression results.

Specifically, there is a close correspondence between the strategy’s average return and the estimated slope from our panel regression in equation (7). Recall from equation (8) that the estimated slope \hat{b} from this regression is a weighted average of the fund-specific slope estimates \hat{b}_i from regression (1). It follows immediately from equation (1) that

$$\hat{b}_i = \frac{\text{Cov}(R_{i,t}, X_{i,t-1})}{\text{Var}(X_{i,t-1})} = \frac{\hat{\sigma}_{RX,i}}{\hat{\sigma}_{x_i}^2}, \quad (12)$$

where the last equality defines $\hat{\sigma}_{RX,i}$. Combining equations (8), (9), and (12), we obtain

$$\hat{b} = \frac{1}{\sum_{n=1}^N T_n \hat{\sigma}_{x_n}^2} \sum_{i=1}^N T_i \hat{\sigma}_{RX,i}. \quad (13)$$

This slope estimate turns out to be proportional to the dollar-weighted average return on our portfolio of fund-level timing strategies, as we show next. For any fund i , the average return on the fund's long-short timing strategy from equation (10) is given by

$$\bar{R}_i^{(dif)} = \frac{1}{T_i} \sum_{t=1}^{T_i} R_{i,t}^{(dif)} = \frac{1}{T_i} \sum_{t=1}^{T_i} (\omega_{i,t-1} - \bar{\omega}_i) R_{i,t}, \quad (14)$$

which follows from equation (11). Recognizing that $X_{i,t-1}$ in equation (7) and $\omega_{i,t-1}$ in equation (10) denote the same quantity, we can rewrite equation (14) as

$$\bar{R}_i^{(dif)} = \hat{\sigma}_{RX,i}, \quad (15)$$

which is the sample covariance defined in equation (12). Combining equations (12) and (15), we can write $\bar{R}_i^{(dif)} = \hat{b}_i \hat{\sigma}_{x_i}^2$. The average return of the long-short timing strategy for fund i is equal to the slope from regression (1) multiplied by the variance of fund i 's turnover.

Finally, we calculate the dollar-weighted average return on our portfolio of fund-level timing strategies. With the help of equations (13) and (15), we obtain

$$\frac{1}{\sum_{i=1}^N T_i} \sum_{i=1}^N \sum_{t=1}^{T_i} R_{i,t}^{(dif)} = \hat{b} \left(\frac{\sum_{i=1}^N T_i \hat{\sigma}_{x_i}^2}{\sum_{i=1}^N T_i} \right). \quad (16)$$

This is the equivalence result mentioned earlier: The strategy's dollar-weighted average return is equal to the estimate of the slope from our panel regression multiplied by the average variance of fund turnover. The latter cross-fund average is weighted by the funds' history lengths, and each turnover variance is a within-fund time-series variance.

The above equivalence can be easily verified in our tables. The left-hand side of equation (16) is 0.0235% per month; see the all-all cell in Panel A of Table 9. The right-hand side is the product of two quantities. The first one, \hat{b} , is 0.00123; see the bottom left cell of Table 1. (Month fixed effects must be excluded for the equivalence to hold.) The second quantity is the average variance of turnover, which is 0.438²; see the all-all cell in Panel B of Table 3. The product of the two quantities is 0.0235%. Not only the estimates but also the t -statistics of the slope and the average return match very closely ($t \approx 6.6$ for both).

The equivalence result adds to the interpretation of our empirical evidence. Thanks to this result, the investment performance of our timing strategy provides a direct and novel perspective on the economic significance of the turnover-performance relation described by our regressions. The fact that the timing strategy produces such an impressive Sharpe ratio implies that the turnover-performance relation is highly economically significant.

The equivalence result in equation (16) generalizes well beyond our specific setting. Any panel regression of asset returns on lagged variables and asset fixed effects can be interpreted

as a timing investment strategy. For example, one could replace mutual funds with individual stocks to describe a timing investment strategy in stocks. To our knowledge, this equivalence is new to the literature.

5.2. A Cross-Sectional Investment Strategy

We also consider a feasible cross-sectional investment strategy that has a timing element to it. At the beginning of each month t , we sort funds into three portfolios based on the ratio of a fund's recent turnover, $FundTurn_{i,t-1}$, to its trailing historical average. We record the portfolios' returns during month t , at the end of which we rebalance.

Panel A of Table 10 reports the average benchmark-adjusted gross returns of the three fund portfolios from 1979 to 2011. The high-turnover portfolio has the highest average return in the full sample, 0.0626% per month, while the return of the low-turnover portfolio is the lowest. The difference between the two averages, 0.0524% per month, is statistically significant ($t = 2.58$). These results show that funds whose turnover is high by their own historical standards tend to outperform funds whose turnover is low.

Panel A also shows the same portfolios' average returns calculated over two subsets of months. All months from 1979 to 2011 are split into two groups based on whether $Sentiment_t$ is above or below its full-sample median. Funds perform well in months immediately following high-sentiment months, and they perform especially well if they trade more than usual. After high-sentiment months, the high-turnover fund portfolio delivers an average benchmark-adjusted gross return of 0.1329% per month, or 1.59% per year. This return exceeds the low-turnover portfolio's average return in the same months by a significant 0.0874% per month, or 1.05% per year. These results suggest that funds trading more than usual tend to perform especially well when sentiment is high, consistent with the presence of more profit opportunities in such periods.

While Panel A reports results based on gross fund returns, which are relevant for assessing managerial skill, Panel B reports analogous results based on returns net of fees, which are relevant for fund investors. All high-minus-low differences are very similar when computed from net returns, reinforcing the conclusions from Panel A. The main incremental value of Panel B is to show the net returns of long-only investment strategies that are feasible from the investors' perspective. The results will disappoint investors. Even though the high-turnover portfolio outperforms the low-turnover portfolio by 0.0537% per month ($t = 2.64$), both portfolios' average benchmark-adjusted net returns are negative; e.g., the high-

turnover portfolio's return is -0.320% per month ($t = -0.92$). The same portfolio's return following high-sentiment months is 0.0442% per month, which is positive but not statistically significant ($t = 0.75$). These results suggest that fund managers are skilled, but their fees are so high that investors cannot benefit from this skill, at least not by following our simple cross-sectional investment strategy.

To summarize, the cross-sectional strategy cannot be profitably exploited by investors, but it produces some significant long-short differences, consistent with the presence of skill. These results complement those based on the timing strategy, which is more directly motivated by our regression evidence. Both strategies provide useful additional perspectives on the economic significance of the turnover-performance relation.

6. Conclusions

We present novel evidence of skill among active mutual funds. Funds have the ability to identify time-varying profit opportunities and adjust their trading activity accordingly. The result is a positive turnover-performance relation: funds perform better after trading more. This time-series relation is stronger for funds that charge higher fees, suggesting that higher-fee funds are more skilled at identifying time-varying profit opportunities. The relation is also stronger for smaller funds, suggesting that such funds are better able to exploit those opportunities, consistent with fund-level decreasing returns to scale.

We also identify a common component of funds' trading that 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, suggesting that they perceive more profit opportunities in such periods. Indeed, the common component of trading positively predicts fund returns. This predictive power weakens in periods when funds act more in concert, consistent with industry-level decreasing returns to scale. The predictive power strengthens when the common component is constructed only across funds in the same size and fee category, suggesting differentiation in profit opportunities across categories. An investment strategy directly motivated by our regressions produces a high Sharpe ratio, highlighting the economic significance of the turnover-performance relation.

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 would also benefit from responding to turnover. Another promising direction is to go beyond turnover and analyze the funds' trading activity in more detail. 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

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 ,

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

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

$$\hat{b}_i = \frac{1}{\hat{\sigma}_{x_i}^2} \left(\frac{x_i'y_i}{m_i} - \bar{x}_i\bar{y}_i \right) , \tag{17}$$

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

$$\begin{bmatrix} \hat{a}_1 \\ \vdots \\ \hat{a}_N \\ \hat{b} \end{bmatrix} = (X'X)^{-1}X'y . \tag{18}$$

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

$$\hat{b} = \sum_{i=1}^N w_i \hat{b}_i, \quad (19)$$

where

$$w_i = \frac{m_i \hat{\sigma}_{x_i}^2}{\sum_{k=1}^N m_k \hat{\sigma}_{x_k}^2}. \quad (20)$$

Proof. First observe

$$\begin{aligned} X'X &= \begin{bmatrix} \iota'_1 & 0 & \cdots & 0 \\ 0 & \iota'_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & & & \iota'_N \\ x'_1 & x'_2 & \cdots & x'_N \end{bmatrix} \begin{bmatrix} \iota_1 & 0 & \cdots & 0 & x_1 \\ 0 & \iota_2 & & \vdots & x_2 \\ \vdots & & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & \iota_N & x_N \end{bmatrix} \\ &= \begin{bmatrix} m_1 & 0 & \cdots & 0 & \iota'_1 x_1 \\ 0 & m_2 & & \vdots & \iota'_2 x_2 \\ \vdots & & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & m_N & \iota'_N x_N \\ \iota'_1 x_1 & \iota'_2 x_2 & \cdots & \iota'_N x_N & x'x \end{bmatrix} \\ &= \begin{bmatrix} D & v \\ v' & q \end{bmatrix}, \end{aligned} \quad (21)$$

and therefore

$$(X'X)^{-1} = \begin{bmatrix} D^{-1} + D^{-1}v(q - v'D^{-1}v)^{-1}v'D^{-1} & -D^{-1}v(q - v'D^{-1}v)^{-1} \\ -(q - v'D^{-1}v)^{-1}v'D^{-1} & (q - v'D^{-1}v)^{-1} \end{bmatrix}. \quad (22)$$

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

$$D^{-1}v = \begin{bmatrix} (\iota'_1 x_1)/m_1 \\ \vdots \\ (\iota'_N x_N)/m_N \end{bmatrix} = \begin{bmatrix} \bar{x}_1 \\ \vdots \\ \bar{x}_N \end{bmatrix} = \bar{x}, \quad (23)$$

and that

$$\begin{aligned} q - v'D^{-1}v &= x'x - \bar{x}'D\bar{x} \\ &= x'_1 x_1 + \cdots + x'_N x_N - m_1 \bar{x}_1^2 - \cdots - m_N \bar{x}_N^2 \\ &= m_1 \left(\frac{x'_1 x_1}{m_1} - \bar{x}_1^2 \right) + \cdots + m_N \left(\frac{x'_N x_N}{m_N} - \bar{x}_N^2 \right) \\ &= m_1 \hat{\sigma}_{x_1}^2 + \cdots + m_N \hat{\sigma}_{x_N}^2. \end{aligned} \quad (24)$$

Also,

$$X'y = \begin{bmatrix} \iota'_1 & 0 & \cdots & 0 \\ 0 & \iota'_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & & & \iota'_N \\ x'_1 & x'_2 & \cdots & x'_N \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} \iota'_1 y_1 \\ \iota'_2 y_2 \\ \vdots \\ \iota'_N y_N \\ x'y \end{bmatrix}. \quad (25)$$

The last element of the pooled least-squares estimator in (18) can now be computed by pre-multiplying the vector in (25) by the last row of the matrix in (22), using (23) and (24) and then (17), 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.

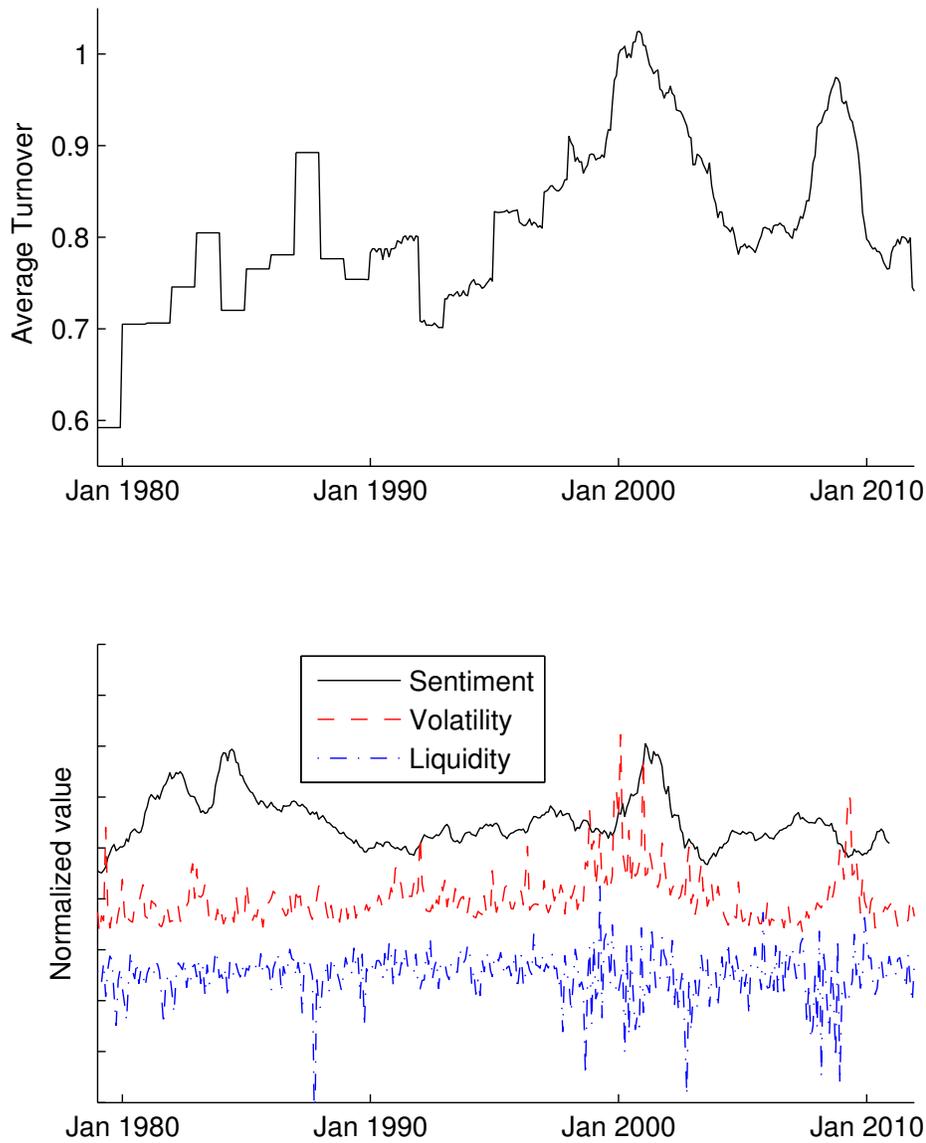


Figure 1. Average Turnover, Sentiment, Volatility, and Liquidity over time. Panel A plots the time series of $AvgTurn_t$, the equal-weighted average turnover across sample funds in the 12-month period that includes month t . Panel B plots the time series of *Sentiment* (from Baker and Wurgler, 2007); *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 $GrossR_{i,t}$, fund i 's benchmark-adjusted gross return in month t , on $FundTurn_{i,t-1}$, fund i 's lagged turnover. The four regressions differ only in their treatment of fixed effects. Heteroskedasticity-robust t -statistics clustered by sector \times month are in parentheses, where "sector" is defined as Morningstar style category. Data are from 1979–2011. There are 285,897 fund-month observations in the panel.

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

Table 2
Turnover-Performance Relation in Fund-Size and Expense-Ratio Categories

This table shows regression slopes of benchmark-adjusted gross fund returns on lagged fund turnover. We estimate the regression in subsamples based on funds' size and expense ratio. All slopes are from panel regressions of $GrossR_{i,t}$ on fund fixed effects, dummy variables for month-by-month terciles of fund expense ratio and/or lagged fund size, and those same dummy variables interacted with $FundTurn_{i,t-1}$. To save space, we tabulate only the slopes on the $FundTurn_{i,t-1}$ variables. "High-Low" is the difference in slope between high and low expense-ratio funds. "Small-Large" is the difference in slope between small and large funds. Heteroskedasticity-robust t -statistics clustered by sector \times month are in parentheses. Data are from 1979–2011.

Fund Size	Fund Expense Ratio				
	All	High	Medium	Low	High-Low
All	0.00123 (6.63)	0.00170 (6.38)	0.00094 (4.62)	0.00058 (2.84)	0.00112 (4.06)
Small	0.00186 (7.56)	0.00191 (5.91)	0.00240 (5.78)	0.00054 (1.72)	0.00138 (3.11)
Medium	0.00086 (3.74)	0.00126 (3.21)	0.00070 (2.70)	0.00029 (0.94)	0.00097 (1.96)
Large	0.00043 (1.46)	0.00136 (2.22)	-0.00015 (-0.47)	0.00046 (1.49)	0.00090 (1.59)
Small-Large	0.00143 (4.11)	0.00055 (0.81)	0.00255 (4.83)	0.00007 (0.18)	0.00145* (3.55)

* Small/High – Large/Low

Table 3
Properties of Fund Turnover in Fund-Size and Expense-Ratio Categories

Each panel shows statistics on annual fund turnover in the full sample as well as in subsamples based on terciles of fund expense ratio and/or lagged fund size. Panel A shows average annual fund turnover. Panel B shows the square root of average within-fund variance of annual turnover, weighting each fund by its history length. Equivalently, Panel B shows the standard deviation of fund-demeaned turnover, pooling all fund/years. Panel C shows the correlation between the current and previous year's fund-demeaned turnover, pooling all fund/years. Heteroskedasticity-robust t -statistics clustered by fund are in parentheses. To test significance in Panel B, we regress squared, fund-demeaned turnover on subsample dummy variables. To test significance in Panel C, we normalize by dividing fund-demeaned turnover by its within-subsample standard deviation, then we regress this turnover variable on its one-year lag interacted with subsample dummy variables. Note that the regression slope of normalized, fund-demeaned turnover on its lag equals the correlation between fund-demeaned turnover and its lag. Data are from 1979–2011.

Fund Size	Fund Expense Ratio					(t-stat.)
	All	High	Medium	Low	High-Low	
Panel A: Average Fund Turnover						
All	0.848	0.979	0.839	0.730	0.249	(9.22)
Small	0.906	1.010	0.804	0.836	0.174	(3.87)
Medium	0.894	1.030	0.868	0.763	0.268	(6.97)
Large	0.760	0.841	0.836	0.675	0.166	(4.16)
Small-Large (t-statistic)	0.147 (5.67)	0.169 (4.17)	-0.032 (-0.89)	0.161 (3.78)	0.335* (8.83)	
Panel B: Within-Fund Volatility of Turnover						
All	0.438	0.508	0.419	0.378	0.130	(7.02)
Small	0.469	0.547	0.387	0.390	0.157	(5.57)
Medium	0.446	0.514	0.434	0.367	0.147	(6.27)
Large	0.402	0.412	0.428	0.379	0.033	(1.28)
Small-Large (t-statistic)	0.067 (3.69)	0.135 (5.01)	-0.041 (-1.66)	0.011 (0.34)	0.168* (5.78)	
Panel C: Within-Fund Autocorrelation of Turnover						
All	0.497	0.491	0.505	0.496	-0.005	(-0.16)
Small	0.425	0.470	0.340	0.351	0.119	(1.98)
Medium	0.474	0.484	0.502	0.405	0.079	(1.58)
Large	0.590	0.563	0.608	0.589	-0.026	(-0.60)
Small-Large (t-statistic)	-0.165 (-5.13)	-0.093 (-2.00)	-0.268 (-5.13)	-0.238 (-4.16)	-0.119* (-2.76)	

* Small/High – Large/Low

Table 4
Average Fund Returns in Fund-Size and Expense-Ratio Categories

Returns are in units of percent per month. The unit of observation is the fund/month. All t -statistics are clustered by fund and sector \times month. Data are from 1979–2011.

Fund Size	Fund Expense Ratio					(t-stat.)
	All	High	Medium	Low	High–Low	
Panel A: Average Benchmark-Adjusted Gross Return (<i>GrossR</i>)						
All	0.0499	0.0879	0.0394	0.0228	0.0650	(3.54)
Small	0.0673	0.0938	0.0493	0.0342	0.0596	(2.32)
Medium	0.0580	0.1013	0.0557	0.0101	0.0912	(3.67)
Large	0.0276	0.0537	0.0139	0.0259	0.0278	(1.05)
Small–Large (t-statistic)	0.0397 (2.48)	0.0401 (1.35)	0.0354 (1.61)	0.0082 (0.41)	0.0679* (2.89)	
Panel B: Average Benchmark-Adjusted Net Return						
All	-0.0534	-0.0552	-0.0596	-0.0455	-0.0097	(-0.53)
Small	-0.0502	-0.0551	-0.0516	-0.0370	-0.0180	(-0.70)
Medium	-0.0471	-0.0399	-0.0428	-0.0609	0.0210	(0.85)
Large	-0.0623	-0.0811	-0.0840	-0.0399	-0.0412	(-1.56)
Small–Large (t-statistic)	0.0121 (0.75)	0.0260 (0.87)	0.0325 (1.48)	0.0029 (0.14)	-0.0151* (-0.64)	

* Small/High – Large/Low

Table 5
What Explains Average Turnover?

The dependent variable 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. Newey-West standard errors using 60 months of lags are in parentheses. $R^2 - R^2(\text{trend only})$ equals the R^2 from the given regression minus 0.353, the R^2 from a regression on the time trend only. Data are from 1979–2011.

	(1)	(2)	(3)	(4)
$Sentiment_t$	0.0531 (3.17)			0.0487 (4.65)
$Volatility_t$		0.938 (7.23)		0.809 (7.98)
$Liquidity_t$			-0.212 (-4.14)	-0.138 (-4.58)
$Business\ Cycle_t$				-0.00334 (-0.66)
$Market\ Return_t$				0.0171 (0.34)
$Time\ Trend_t$	0.000602 (5.21)	0.000400 (3.88)	0.000459 (3.44)	0.000523 (5.20)
R^2	0.524	0.542	0.377	0.677
$R^2 - R^2(\text{trend only})$	0.171	0.189	0.024	0.324
Observations	372	382	382	372

Table 6
Relation Between Fund Performance and Average Turnover

The dependent variable in each regression model is $GrossR_{i,t}$, fund i 's benchmark-adjusted gross return in month t . $AvgTurn_{t-1}$ is the lagged average turnover across funds. $FundTurn_{i,t-1}$ is fund i 's lagged turnover. $IndustrySize_{t-1}$ is the lagged size of the active mutual fund industry. $AvgCorr_{t-1}$ is the lagged average pairwise correlation in funds' benchmark-adjusted gross returns. Lagged $Sentiment$, $Volatility$, and $Liquidity$ are defined in the previous table. All regressions include fund fixed effects. Heteroskedasticity-robust t -statistics clustered by sector \times month are in parentheses. Data are from 1979–2011.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$AvgTurn_{t-1}$	0.00741 (2.13)	0.00722 (2.04)	0.00873 (2.34)	0.0135 (2.77)	0.0299 (3.22)	0.0261 (2.55)	0.0268 (2.61)
$AvgTurn_{t-1} \times AvgCorr_{t-1}$					-0.217 (-2.69)	-0.277 (-2.93)	-0.267 (-2.82)
$AvgCorr_{t-1}$				-0.0266 (-2.42)	0.158 (2.55)	0.205 (2.83)	0.195 (2.69)
$FundTurn_{i,t-1}$		0.00107 (6.46)	0.00101 (6.21)	0.00101 (6.20)	0.00100 (6.16)	0.00108 (6.47)	*
$IndustrySize_{t-1}$			-0.0218 (-4.26)	-0.0361 (-3.97)	-0.0309 (-3.78)	-0.0156 (-2.28)	-0.0103 (-1.51)
$Sentiment_{t-1}$						0.00224 (3.38)	0.00226 (3.42)
$Volatility_{t-1}$						0.0118 (1.31)	0.0117 (1.30)
$Liquidity_{t-1}$						-0.00333 (-0.92)	-0.00341 (-0.95)
Observations	309,695	284,800	284,800	284,800	284,800	269,056	269,016

* The last column includes 18 additional control variables that are not tabulated. These control variables equal nine dummies for the interaction of fund-size and expense-ratio tercile dummies, and those same nine dummies interacted with $FundTurn_{i,t-1}$.

Table 7
Commonality in Turnover

We measure each fund's correlation between $FundTurn_{i,t}$ and $AvgTurn_t$, and also its correlation between $FundTurn_{i,t}$ and $OwnCellAvgTurn_{i,t}$. $OwnCellAvgTurn_{i,t}$ equals the average turnover of funds in the same size and expense-ratio tercile as fund i in month t . We present the weighted-average correlation across funds, where the weights are the number of observations per fund. We also present the weighted-average correlation within subsamples based on the tercile of the fund's expense ratio and/or lagged size. Data are from 1979–2011.

Fund Size	Fund Expense Ratio			
	All	High	Medium	Low
Panel A: Average Correlation of $FundTurn$ and $AvgTurn$				
All	0.131	0.119	0.139	0.135
Small	0.114	0.085	0.135	0.146
Medium	0.123	0.138	0.123	0.104
Large	0.151	0.150	0.157	0.148
Panel B: Average Correlation of $FundTurn$ and $OwnCellAvgTurn$				
All	0.173	0.150	0.176	0.194
Small	0.138	0.115	0.139	0.185
Medium	0.160	0.158	0.152	0.173
Large	0.213	0.201	0.228	0.209

Table 8

Relation Between Fund Performance and Within-Category Average Turnover

All details are the same as in Table 6, except we now include $OwnCellAvgTurn_{i,t-1}$, the average turnover of funds in the same size and expense-ratio tercile.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$OwnCellAvgTurn_{i,t-1}$	0.00511 (4.16)	0.00398 (7.02)	0.00397 (6.61)	0.00307 (5.72)	0.00297 (5.59)	0.00883 (4.70)	0.00646 (3.11)
$OwnCellAvgTurn_{i,t-1} \times AvgCorr_{t-1}$						-0.0796 (-3.33)	-0.0702 (-2.90)
$AvgCorr_{t-1}$					-0.0293 (-2.64)	0.0367 (2.54)	0.0279 (1.90)
$AvgTurn_{t-1}$		0.00386 (1.13)	0.00378 (1.09)	-0.00361 (-0.91)	0.00182 (0.39)	0.00236 (0.50)	0.00512 (1.08)
$FundTurn_{i,t-1}$			0.000938 (5.72)	0.000978 (5.84)	0.000980 (5.86)	0.000985 (5.89)	*
$IndustrySize_{t-1}$				-0.00666 (-1.24)	-0.0216 (-2.79)	-0.0191 (-2.58)	-0.0146 (-1.96)
$Sentiment_{t-1}$				0.00168 (2.93)	0.00189 (3.11)	0.00196 (3.20)	0.00199 (3.24)
$Volatility_{t-1}$				0.0160 (1.72)	0.0133 (1.46)	0.0126 (1.39)	0.0127 (1.40)
$Liquidity_{t-1}$				-0.00490 (-1.38)	-0.00462 (-1.31)	-0.00419 (-1.18)	-0.00429 (-1.21)
Observations	310,779	309,566	284,800	269,056	269,056	269,056	269,016

* The last column includes 18 additional control variables that are not tabulated. These control variables equal nine dummies for the interaction of fund-size and expense-ratio tercile dummies, and those same nine dummies interacted with $FundTurn_{i,t-1}$.

Table 9
Timing Investment Strategy

This table shows the performance of a timing strategy that invests $\omega_{i,t-1} = FundTurn_{i,t-1}$ dollars in fund i in month t and invests $1 - \omega_{i,t-1}$ dollars in the passive benchmark. The timing strategy's benchmark-adjusted return in month t equals $R_{i,t}^{(tim)} = \omega_{i,t-1}GrossR_{i,t}$. We also examine a related non-timing strategy that invests a constant $\bar{\omega}_i$ dollars in fund i in month t , where $\bar{\omega}_i$ is the average of $\omega_{i,t}$ over time for fund i . The non-timing strategy's benchmark-adjusted return in month t equals $R_{i,t}^{(notim)} = \bar{\omega}_iGrossR_{i,t}$. The difference in benchmark-adjusted return between the timing and non-timing strategies equals $R_{i,t}^{(dif)} = (\omega_{i,t-1} - \bar{\omega}_i)GrossR_{i,t}$. Panels A and B show the average of $R_{i,t}^{(dif)}$ in both the full sample and subsamples based on month-by-month terciles of expense ratios and/or fund size. Panel A treats each fund/month as the unit of observation, thus reporting the average performance on the typical dollar invested. In contrast, Panel B reports the average performance in the typical month. We first compute each month's average $R_{i,t}^{(dif)}$ across funds i , then we average across months t . The t -statistics in parentheses in Panel A take into account that $R_{i,t}^{(dif)}$ may be correlated across funds i in the same sector within a month t . In other words, we cluster by sector \times month. All returns in Panels A and B are in units of percent per month. Data are from 1979–2011.

Fund Size	Fund Expense Ratio				
	All	High	Medium	Low	High-Low
Panel A: Dollar-Weighted Average Excess Timing-Strategy Return					
All	0.0235 (6.53)	0.0462 (6.49)	0.0183 (4.14)	0.0067 (2.19)	0.0395 (5.78)
Small	0.0382 (6.45)	0.0541 (5.11)	0.0356 (4.76)	0.0074 (1.02)	0.0466 (3.68)
Medium	0.0218 (4.14)	0.0404 (3.46)	0.0173 (2.79)	0.0049 (0.98)	0.0355 (2.88)
Large	0.0135 (3.04)	0.0411 (4.21)	0.0057 (0.87)	0.0074 (1.66)	0.0338 (3.67)
Small-Large	0.0247 (3.87)	0.0129 (0.99)	0.0299 (3.27)	0.0000 (0.00)	0.0467* (4.36)
Panel B: Time-Weighted Average Excess Timing-Strategy Return					
All	0.0257 (4.49)	0.0525 (4.15)	0.0208 (2.91)	0.0066 (0.97)	0.0458 (3.85)
Small	0.0175 (1.76)	0.0341 (2.19)	0.0081 (0.50)	0.0025 (0.26)	0.0316 (1.85)
Medium	0.0360 (3.54)	0.0553 (3.04)	0.0229 (2.04)	0.0085 (0.51)	0.0469 (1.93)
Large	0.0197 (3.44)	0.1258 (4.32)	0.0223 (2.14)	0.0044 (0.70)	0.1214 (4.24)
Small-Large	-0.0023 (-0.22)	-0.0917 (-2.89)	-0.0142 (-0.74)	-0.0019 (-0.18)	0.0297* (2.11)

* Small/High – Large/Low

Table 10
Cross-Sectional Investment Strategy

This table shows the average monthly percent benchmark-adjusted fund return on portfolios of mutual funds. Fund returns are gross of fees in Panel A but net of fees in Panel B. At the beginning of each month we sort funds into portfolios based on month-by-month terciles of the ratio of $FundTurn_{i,t-1}$ to the fund's trailing-average turnover. We compute trailing averages using fund data from the beginning of the sample until 24 months before the portfolio-formation month. The High–Low t -statistics in parentheses are clustered by month. The last column contains the p -value from an F -test of whether the three portfolios have the same average benchmark-adjusted return, clustering by month. The rows labeled “High Sentiment” and “Low Sentiment” show the strategy's performance in months after above- and below-median sentiment. Data are from 1979–2011.

Sample months	$FundTurn_{i,t-1}$ /trailing-average turnover				F -test p -value
	Low	Medium	High	High – Low	
Panel A: Gross Returns					
Full Sample	0.0102 (0.31)	0.0498 (1.42)	0.0626 (1.80)	0.0524 (2.58)	0.033
High Sentiment	0.0456 (0.85)	0.1003 (1.69)	0.1329 (2.25)	0.0874 (2.71)	0.028
Low Sentiment	-0.0300 (-0.74)	0.0033 (0.09)	-0.0083 (-0.23)	0.0217 (0.87)	0.249
High–Low	0.0755 (1.13)	0.0970 (1.38)	0.1412 (2.05)	0.0656 (1.61)	
Panel B: Net Returns					
Full Sample	-0.0857 (-2.58)	-0.0440 (-1.25)	-0.0320 (-0.92)	0.0537 (2.64)	0.027
High Sentiment	-0.0471 (-0.88)	0.0094 (0.16)	0.0442 (0.75)	0.0914 (2.82)	0.020
Low Sentiment	-0.1294 (-3.19)	-0.0937 (-2.51)	-0.1095 (-3.04)	0.0199 (0.80)	0.184
High–Low	0.0822 (1.23)	0.1031 (1.47)	0.1537 (2.23)	0.0715 (1.75)	

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