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Abstract

We construct a fund-level measure of managers' ability to identify underpriced securities, and show that the relation between fund turnover and future performance depends on this ability. Higher turnover predicts higher returns for the tercile of funds that hold more underpriced stocks, but lower returns for the tercile of funds that hold more overpriced stocks, when each group is compared to all the other funds. This interactive mechanism is driven by fund purchases, consistent with long-only constraints. It is magnified during periods of high investor sentiment or market volatility, it cannot be explained by fund flows or luck in selecting stocks, and it persists after controlling for established measures of managerial skill, portfolio liquidity, fund activeness, and mispricing. This analysis reveals that the relation between fund turnover and performance arises not only from time-varying profit opportunities, but also from cross-sectional differences in managers' ability to identify underpriced assets.

Key Words: mutual fund performance, active fund management, turnover, stock mispricing, ability to identify mispriced opportunities
JEL Classification: G12, G14, and G23

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1. Introduction

The debate on the value of active management in mutual funds has carried on for decades. As part of this pursuit, previous research has extensively studied how the portfolio turnover of actively managed funds influences subsequent performance. This research is grounded on a common economic intuition: if a fund's active management adds value, then its trading activity should reflect *both the identification and exploitation* of profit opportunities. For example, Chen, Jegadeesh, and Wermers (2000, p. 362) argue, "it is possible that some fund managers are able to routinely identify attractive investment opportunities and hence trade frequently, while managers with more limited skills may be much more cautious in their trades." One prediction from this argument is that greater fund turnover should tend to enhance future performance, on average.

Despite this appealing intuition, previous studies find that the relation between fund turnover and performance is sometimes positive, negative, or insignificant.[1] One possible explanation for these mixed findings is that the relation between turnover and performance may vary systematically across funds (e.g., Pástor, Stambaugh, and Taylor, 2017 and 2020, hereafter PST; Shen, Tong, and Yao, 2021). However, prior work does not distinguish between the ability of funds to *identify* profit opportunities and the intensity with which they trade to *exploit* such opportunities, nor does it examine how the interaction between these two aspects of managerial behavior influences performance. While we expect higher turnover to be associated with greater performance for funds that are more skilled at identifying profit opportunities, this may not be true for funds that are less skilled in that respect, since they may sustain losses when they trade against informed investors.[2] Thus, variation across funds in the ability to *identify* profit opportunities could provide an economic explanation for the mixed evidence in prior studies on the average relation between fund turnover and performance.

We address this limitation of prior research by introducing a new measure of a fund manager's ability to identify underpriced assets, and by studying how this skill interacts with the fund's turnover

[1] For example, see Elton et al. (1993) and Carhart (1997); Chen, Jegadeesh, and Wermers (2000); Dahlquist, Engström, and Söderlind (2000); Wermers (2000); Kacperczyk, Sialm, and Zheng (2005); Edelen, Evans, and Kadlec (2013); and Pástor, Stambaugh, and Taylor (2017).

[2] For example, see Grossman (1976); Grossman and Stiglitz (1980); and Verrecchia (1982).

to explain future performance. In essence, we separate the manager's ability to identify profit opportunities from the intensity of the fund's trading, and examine how these two aspects of managerial behavior interact. In line with our discussion above, we hypothesize that higher turnover should have a stronger positive relation with future performance for funds with greater skills in identifying such opportunities but should have a weaker positive relation, or even a negative relation, for funds with lower opportunity identification skills.

We begin by constructing a fund-level measure of managers' ability to identify underpriced assets, which reflects the extent to which the stocks held by a fund are undervalued. Specifically, we rely on the percentile-based metric of monthly mispricing for individual stocks developed by Stambaugh, Yu, and Yuan (2015, labeled $MISP$), which ranges from 0 for the most underpriced stocks to 100 for the most overpriced stocks. We then focus on 100 - $MISP$, so that *higher values* indicate *greater skill in identifying undervalued* stocks for funds to purchase. Finally, we aggregate this monthly measure across stocks held at the fund level, weighted by the fund's most recent quarterly holdings of each stock, to produce a monthly metric for the degree of fund underpricing (labeled FU). The basic idea is that funds with greater ability to identify profit opportunities should be more likely to identify and hold securities that are more undervalued, and should thus exhibit higher values of FU. We then examine whether the predictive relation between a fund's turnover (measured by the churn rate, CR) and future performance depends on the level of fund underpricing (FU).

Our central finding is that the *interaction* between FU and CR positively predicts performance, which implies that the profitability of fund turnover itself depends on the fund's ability to identify underpriced stocks (FU). Digging deeper into this interactive effect, we show that higher turnover (CR) is associated with *higher* returns for the tercile of funds that hold more *underpriced* stocks (with *high* FU), but with *lower* returns for the tercile of funds that hold more *overpriced* stocks (with *low* FU), when each group is compared to all other funds. These findings indicate that, when funds with weaker opportunity identification skills (low FU) misidentify opportunities and hold more overvalued securities, more active trading (CR) is associated with relatively weaker performance. In contrast, for

funds with a stronger ability to identify undervalued opportunities (high FU), more active trading allows them to exploit those opportunities to generate relatively better performance.

The economic magnitude of this effect is significant: a one-standard-deviation increase in turnover is associated with annual performance that is 34.5 basis points (bps) *higher* for the tercile of underpriced funds with high FU, but with annual performance that is 33.3 bps *lower* for the tercile of overpriced funds with low FU, when each group is compared with all other funds.[3] This heterogeneity in the relation between turnover and performance across funds with differing abilities to identify undervalued stocks helps to reconcile the mixed evidence from prior research that focuses on the overall relation between turnover and performance. To our knowledge, this is the first study to directly measure a fund's ability to identify underpriced assets and document that the predictive relation between the fund's turnover and future performance is conditional on this ability.

We further decompose total fund turnover into its buying and selling components, and examine whether this interactive effect of fund underpricing and turnover (FU × CR) on performance is driven by trading on the buy side or the sell side. The notion is that, when funds are better at identifying undervalued stocks (i.e., have higher FU), they should benefit mainly from buying rather than selling. Indeed, we show that FU primarily interacts with turnover from the buy side to amplify the relation between turnover and future performance. This evidence suggests that, when funds are more skilled at identifying undervalued stocks, active *buying* increases the fund's exposure to those opportunities, which ultimately leads to better performance. In contrast, active *selling* may not similarly enhance performance, since funds that might be able to identify undervalued stocks may not be able to exploit such opportunities through selling. Similarly, long-only funds that might be able to identify overvalued securities cannot exploit them through short selling.

In our main analysis, we use style-by-time fixed effects to capture variation across funds that operate within the same style categories at the same point in time. This choice ensures that the

[3] The economic magnitude of our findings is comparable to the differences in performance documented in prior studies that compare funds with high versus low levels of activeness, turnover, or other characteristics, such as Avramov et al. (2020), Cremers and Petajisto (2009), Pastor, Stambaugh, and Taylor (2017), and Shen et al. (2021).

interactive effect between fund underpricing and turnover (FU × CR) that we focus on is not simply driven by time-varying market conditions or time-varying shocks that are common to funds within the same style category. Such market conditions could represent common style-specific trading opportunities that vary over time. Instead, our results reflect cross-sectional variation in the ability of funds in the same style space and time frame to *identify* underpriced stocks, as well as the intensity with which they trade to *exploit* such perceived opportunities.

Further analysis establishes that the positive interactive effect of fund underpricing (FU) on the relation between turnover (CR) and performance is robust when we employ alternative fixed-effect structures, such as separate (non-interacted) style and time fixed effects, or fund fixed effects alone, or both fund and time fixed effects. The fact that our key results hold when we account for various forms of both fund and time fixed effects indicates that the effect of fund underpricing on the relation between turnover and performance in the cross-section is also present within funds over time. In other words, during periods when a given fund's portfolio reflects greater underpricing (higher FU), fund turnover also has stronger positive predictive power for future performance, in contrast to other periods when that same fund has lower FU. However, within-fund variation in FU over time does not necessarily imply changes in a fund's underlying ability to identify profit opportunities. Rather, it reflects variation over time in the extent to which any such ability is reflected in the fund's portfolio.[4]

We explore various alternative potential explanations for our main finding that the relation between fund turnover and performance is conditional on a fund's ability to identify underpriced assets. First, we rule out the possibility that our evidence may be due to our proxy for fund underpricing (FU) simply being driven by luck in a fund manager's ability to identify underpriced stocks, rather than persistent skill. To that end, we show that FU is highly persistent for the subset of skilled managers, since funds ranked in the top decile by FU in one month have a strong tendency to remain in the top

[4] Such variation may arise over time because funds might change their reliance on stock-picking versus timing abilities, and thereby adjust whether they focus more on firm-level versus macro information (Kacperczyk, van Nieuwerburgh, and Veldkamp, 2014), or because non-information-driven trading related to fund flows, liquidity needs, window dressing, or tax considerations may alter the exposure of the fund portfolio to identified mispricing opportunities (Edelen, 1999; Agarwal, Gay, and Ling, 2014; Poterba and Weisbenner, 2001).

one or two deciles over the next twelve months. Second, we rule out the possibility that our results are spurious, perhaps due to certain methodological choices we make. We accomplish this task by conducting a placebo test for the sample of index funds which passively replicate a benchmark index, and thus cannot actively exploit perceived mispricing opportunities through trading. As expected, we find no significant interactive effect between FU and turnover in explaining future performance for index funds. Third, we document that our main results are not due to turnover being induced by large fund flows, since we show that the interactive effect is not significantly different across periods with normal fund flows versus periods with either large inflows or large outflows. Finally, we rule out the possibility that our main results could simply reflect temporary price pressure due to aggressive purchases by funds with greater skills in identifying underpriced opportunities (higher FU), which might enhance short term returns in the following month but should be followed by reversals in subsequent months. Instead, we show that the significant positive relation between the interaction term (FU × CR) and performance persists for up to three months and then slowly decays toward zero, without reversing to a significant negative effect.

In additional analysis, we extend the work of PST (2017) who show that funds trade more aggressively and more profitably when market dislocations are greater, during periods of market stress proxied by high sentiment, volatility, or illiquidity. While PST focus on how such time-varying aggregate profit opportunities affect fund trading and its profitability, we examine whether these same market conditions magnify cross-sectional differences in the profitability of turnover based on a fund's ability to identify underpriced assets. In particular, we interact our main variables of interest (i.e., FU, CR, and FU × CR) with indicator variables for periods of high investor sentiment, market volatility, or illiquidity. During such periods of high market sentiment or volatility, the relation between turnover and performance is significantly more positive for funds with greater underpricing (FU). This evidence suggests that, when overall mispricing opportunities are likely to be greater, the differences in the profitability of turnover across funds with stronger versus weaker opportunity identification skills becomes more pronounced. This evidence complements PST by showing that, when overall investment

opportunities are likely to be more plentiful, the profitability of a fund's trading activity is even more dependent on its ability to identify those opportunities.[5]

Our main results also withstand two key robustness checks. First, they hold across various measures of fund performance, including the fund's monthly gross return, CAPM alpha, Carhart (1997) four-factor (FF4) alpha, Fama and French (2016) five-factor (FF5) alpha, the alpha of a liquidity factor model (FFL) that includes the Carhart (1997) four factors plus the liquidity factor of Pástor and Stambaugh (2003), and the alpha of a mispricing factor model (FFM) that includes the Carhart (1997) four factors plus a mispricing factor based on Stambaugh and Yuan (2017).[6] Second, we establish that the association between a fund's ability to identify underpriced assets (FU) and the profitability of turnover remains robust when we account for alternative fund attributes related to managerial skill, portfolio liquidity, fund activeness, and fund mispricing, along with their respective interactions with turnover. These attributes include the 'expense ratio' proxy used by PST (2017), past fund performance (Cohen, Coval, and Pástor 2005; Shen, Tong, and Yao 2021), the portfolio liquidity measure of PST (2020), the 'active weight' measure of Doshi, Elkamhi, and Simutin (2015), the 'active share' measure of Cremers and Petajisto (2009), and the 'active fund overpricing' measure of Avramov et al. (2020). This evidence is consistent with the view that our measure (FU) more directly captures managers' skill in identifying profit opportunities in comparison to these alternative measures, and it thus plays a more important role in explaining the heterogeneity in the relation between fund turnover and performance.

Our study contributes to the broader literature on active fund management that examines the relation between turnover and performance for actively managed funds in the cross-section. The evidence from this literature is mixed, with some studies finding a positive relation (e.g., Dahlquist, Engström, and Söderlind, 2000; Chen, Jegadeesh, and Wermers, 2000; and PST, 2017[7]), some finding

[5] We do not find similar results when we use the aggregate measure of illiquidity from Pástor and Stambaugh (2003) to proxy for periods of greater mispricing opportunities. We conjecture that, although periods with heightened illiquidity could provide more mispricing opportunities consistent with PST, trading conditions might also deteriorate with greater overall illiquidity, thus limiting the extent to which these opportunities may be exploited through trading.

[6] The result that the FU × CR interaction term remains significant after controlling for exposure to the Stambaugh and Yuan (2017) mispricing factor suggests that the conditional profitability of turnover extends beyond passive exposure to the anomaly-based mispricing premium, and is instead driven by the presence of managerial opportunity-identification skill.

[7] Although PST (2017) emphasize the within-fund relation between turnover and performance, they also document a cross-sectional, albeit weaker, relation between turnover and performance.

a negative relation (e.g., Elton et al., 1993, and Carhart, 1997), and others finding no relation (e.g., Wermers, 2000; Kacperczyk, Sialm, and Zheng, 2005; and Edelen, Evans, and Kadlec, 2013). Our analysis helps to reconcile this mixed evidence by focusing on the distinction between the ability of funds to *identify* profit opportunities (FU) and the intensity with which they trade (CR) to *exploit* such opportunities. We show that the average relation between turnover and performance across all funds masks substantial heterogeneity in this relation, by showing that this overall relation depends on the ability of a fund to identify profitable investment opportunities. Specifically, higher turnover has a relatively stronger predictive relation with future performance for funds with greater opportunity identification skills but a relatively weaker relation, or even a negative relation, for funds with lower such skills. Furthermore, this conditional relation is present not only across funds, but also within funds over time since, for a given fund, turnover has stronger predictive power for performance during periods when its portfolio reflects greater underpricing. Thus, our findings also help to reconcile the prior mixed evidence for the cross-sectional relation between turnover and performance with the positive within-fund relation documented by PST (2017).

Our study also builds upon prior research which shows that the relation between turnover and performance varies across funds with different attributes. For example, PST (2017) find a stronger relation among funds with high expense ratios; PST (2020) document a stronger relation among funds holding less-liquid portfolios; and Shen, Tong, and Yao (2021) document a stronger relation among funds with better past performance. Taken together, these prior findings indirectly raise the possibility that heterogeneity in the profitability of turnover across funds may reflect cross-sectional differences in the abilities of funds to identify profitable investment opportunities.

We directly examine this possibility by constructing a proxy for the ability of fund managers to identify profit opportunities, and distinguishing between this ability and the intensity with which they trade on such perceived opportunities. Fund expenses may indirectly proxy for managerial skill, while portfolio liquidity reflects trading costs. Past performance, in turn, captures the combined outcomes of various aspects of managerial skill as well as luck (e.g., Barras, Scaillet, and Wermers

2010; Fama and French 2010).[8] In contrast, our measure of fund underpricing (FU) is designed to directly capture managers' ability to identify undervalued securities. We show that higher turnover is associated with relatively better performance for funds with greater opportunity identification skills, but it is associated with relatively weaker performance for funds with lower such skills. Importantly, the positive interaction between FU and turnover remains statistically significant even after controlling for fund expenses, portfolio liquidity, and past performance, as well as their respective interactions with turnover. Thus, our findings advance the literature by identifying opportunity identification skill as an important economic source of heterogeneity in the turnover–performance relation that is not captured by the fund characteristics and explanations emphasized in prior research.

2. Sample and Variable Construction

2.1 Data Sources, Sample Description, and Control Variables

We obtain mutual fund characteristics from the CRSP Mutual Fund Database (MFDB) and fund portfolio holdings from the LSEG Mutual Fund Holdings Database (S12 Master File). These databases encompass nearly all U.S.-based mutual funds that have existed since 1980, and are largely free from survivorship bias. We link the mutual funds from these two databases using the WRDS MFLINKS database. We follow standard filters from the literature to identify open-end domestic equity funds (e.g., Kacperczyk, Sialm, and Zheng, 2008, Appendix A, p. 2412). In particular, our domestic equity mutual funds sample includes funds in the following investment style categories: micro-cap (EDCI), small-cap (EDCS), mid-cap (EDCM), large-cap (EDCL), growth-and-income blend (EDYB), growth-oriented (EDYG), and income-oriented (EDYI). In addition, we exclude funds that hold less than 80% or more than 105% in stocks, on average (Kacperczyk, Sialm, and Zheng, 2008). Since our focus is on actively managed mutual funds, we exclude index funds from our main

[8] Shen, Tong, and Yao (2021) use the return gap of Kacperczyk, Sialm, and Zheng (2008) to provide evidence that short-term stock-selection information contributes to their findings. However, the return gap reflects not only the benefits of unobserved trading activities but also their associated transaction costs. As a result, their evidence does not clearly distinguish short-term stock-selection skill from trading-cost considerations, which may overlap with the liquidity-related trading frictions emphasized by PST (2020).

analysis.[9] Similarly, we leave out target-date funds.[10] To avoid incubation bias, we exclude small funds with total net assets less than $5 million (Evans, 2010) and exclude the first 12 months of observations for each fund (Dong, Feng, and Sadka, 2019). Finally, to avoid using stale portfolio holdings information, we treat each fund's holdings report as valid for no more than six months after the report date, or until the next holdings report becomes available, whichever occurs first.

For funds with multiple share classes, we compute fund-level variables by aggregating their holdings across share classes. Specifically, we sum the TNA across all share classes to obtain the TNA for the fund. For other fund attributes like turnover and expenses, we use the TNA-weighted average across all share classes. The weights are based on the previous month's total net assets for each share class in the same fund.[11]

Throughout the analysis, we control for a set of fund characteristics commonly used in the literature, including the fund's total net assets (TNA), expense ratio, return volatility, fund flow, and fund family size. We also examine several alternative measures of performance, including monthly fund gross returns (adding back expenses), CAPM alpha, Carhart (1997) four-factor (FF4) alpha, and Fama and French five-factor (FF5) alpha, as well as the alpha of the alternative five-factor model (FFL) of Pástor and Stambaugh (2003) that includes the Carhart (1997) four factors plus their liquidity factor.

2.2 Fund Underpricing and Turnover

Our proposed measure of fund underpricing, FU, is the weighted average of firm-specific underpricing scores across all stocks held by a given fund in a given month, computed as follows:

$$FU_{f,t} = \sum_{i=1}^{N_f} w_{i,t}^{f} \left(100 - MISP_{i,t}\right), \quad (1)$$

[9] For example, see Busse and Tong (2012), Ferson and Lin (2014), and Jones and Mo (2021). We identify index funds with an "index fund flag" of B, D, or E in CRSP. We also identify funds with ETF flag as "F" or "N." Index funds and exchange-traded funds (ETFs) are also identified using keywords in fund names, including exchange-traded, exchange traded, etf, dfa, index, inde, indx, ind_, inx, idx, dow jones, dow, dj, ishare, s&p, s &p, s& p, s & p, s and p, wilshire, russell, russ, msci, bloomberg, nasdaq, kbw, nyse, stoxx, ftse, composite, and numeric benchmarks 400, 500, 600, 900, 1000, 1500, 2000, 3000, and 5000. We also apply manual checks for index funds within domestic equity funds.

[10] Target-date funds are identified based on the following keywords appearing in their names: 2055, 2050, 2045, 2040, 2035, 2030, 2025, 2020, 2015, 2010, 2005, and Target.

[11] Stock data are obtained from CRSP. The delisting is adjusted by using the CRSP delisting return, where available, or a return of -0.30 for all relevant delisting codes (DLSTCD of 500, 520, 551-573, 579, 574, and 584).

where ${w_{i,t}}^f$ is the market value weight (in percentage) of stock *i* in fund *f*'s portfolio based on holdings from the end of the most recent quarter prior to month *t*, and N_f denotes the number of stocks in the portfolio of fund *f* in each quarter. A higher value of $MISP_{i,t}$ indicates more *over*pricing for a given stock, with scores that range from 0 (for the most underpriced) to 100 (for the most overpriced). Therefore, higher values of $\left(100 - MISP_{i,t}\right)$ reflect greater stock *under*pricing. Stock-level mispricing data $\left(MISP_{i,t}\right)$ are obtained from Stambaugh, Yu, and Yuan (2015) and Han et al. (2022), from 1963 to 2019. We extend these stock mispricing data $\left(MISP_{i,t}\right)$ from 2020 through 2024 by following the methodology in Stambaugh, Yu, and Yuan (2015).[12]

Note that our weighted average measure of a fund's underpricing $\left(FU_{f,t}\right)$ varies across quarters due to quarterly changes in the fund's holdings, and across months (*t*) due to changes in both the mispricing scores $\left(MISP_{i,t}\right)$ and the market values of the weights (${w_{i,t}}^f$) for stocks held by the fund in the prior quarter. Thus, $FU_{f,t}$ effectively (if imperfectly) reflects the ability of fund managers to identify underpricing opportunities during month *t*. Because data on fund holdings are available quarterly since 1980, the overlap in data availability with $MISP_{i,t}$ establishes the sample period for our fund underpricing measure (FU) from 1980 through 2024.

Fund portfolio turnover is defined as the churn rate (CR), which is the minimum of a fund's total purchases or sales (CR_Buy or CR_Sell) made in the most recent quarter prior to month *t*, scaled by average total holdings over the past two quarters. This definition follows Yan and Zhang (2009), who note that the churn rate limits the impact of fund flows on portfolio turnover since it relies on the minimum of purchases and sales, rather than their sum as in Gaspar, Massa, and Matos (2005).

2.3 Sample Characteristics

Table 1 reports summary statistics for the fund characteristics across the entire sample of panel data, from 1980 to 2024. The final sample consists of 3,797 unique actively managed U.S. equity funds and 568,528 fund-month observations. On average, fund TNA is $1.737 billion, with a mean fund

[12] We thank Robert Stambaugh and Guofu Zhou for providing stock-level mispricing data (MISP) from 1963 – 2019 (see https://finance.wharton.upenn.edu/~stambaug/ and https://apps.olin.wustl.edu/faculty/zhou/zpublications.html).

family size of $39.5 billion, and a mean monthly net return of 0.84%. The average expense ratio is 1.15%, the average return volatility is 4.97%, and average monthly fund flow is -0.06% of the fund's total assets. The average fund underpricing measure (FU) of 59.14 is slightly more than 50, suggesting that funds tend to hold more underpriced stocks than overpriced stocks, on average. The mean total portfolio turnover (CR) is 5.22% of the fund's total assets, with average buy-side turnover (CR_Buy) of 8.82% and sell-side turnover (CR_Sell) of 11.12%, respectively.

Table 2 presents average fund attributes for deciles of funds within each fund investment style and month, based on our measure of fund underpricing (FU). Consider the behavior of fund turnover (CR) as we move from decile portfolios with low to high FU. The bottom row (H-L FU) indicates that funds with the most underpriced portfolios (with high FU) have significantly greater turnover (CR) relative to funds with the most overpriced portfolios (with low FU), although CR does not increase monotonically across FU deciles. This non-monotonic rise in total turnover tends to be driven by significantly higher buy-side turnover (CR_Buy) for funds with high versus low FU, while the analogous difference (H-L FU) for sell-side turnover (CR_Sell) is insignificant. This stronger association between FU and CR_Buy is consistent with the notion that funds with greater ability to identify undervalued stocks exploit these opportunities through active buying rather than selling.

Funds with the highest ability to identify underpriced stocks (FU) also have significantly higher returns, on average. This differential ability is further reflected in expense ratios, consistent with fund investors paying higher fees for funds that outperform through superior ability to identify profit opportunities (PST, 2017). Funds with high FU also exhibit larger inflows, which is consistent with investors moving money into funds with greater ability to identify such opportunities. In addition, funds with either more underpriced or overpriced portfolios tend to have smaller fund size (Log(TNA)), relative to funds with medium FU, consistent with larger funds being more constrained in exploiting extreme mispricing opportunities due to liquidity concerns and trading costs (PST, 2015). Funds with the most under- and over-priced portfolios also hold fewer stocks, indicating that extreme FU values are associated with more concentrated portfolios and more active bets. Interestingly, funds with more

underpricing exhibit lower return volatility, suggesting that the greater performance of high-FU funds is not driven by greater total risk.

3. Main Analysis

3.1 The Relation between Turnover and Performance for Funds with Low or High FU

In this subsection, we estimate panel regressions to examine whether the relation between fund turnover (CR) and future performance is different for subsets of funds with low versus high ability to identify underpriced investment opportunities (FU). Specifically, every month within each investment style category, we first sort all funds into terciles by FU and we classify funds as underpriced (overpriced) if FU is in the top (bottom) tercile. We then examine whether the predictive relation between fund turnover (CR) and future performance is significantly different for underpriced funds (with high FU) or overpriced funds (with low FU), using the following regression model:

$$FF5\ Alpha_{f,t+1} = \alpha^0 + \beta 1\ Low_FU_{f,t} + \beta 2\ High_FU_{f,t} + \beta 3\ CR_{f,t} + \beta 4\ Low_FU_{f,t} \times CR_{f,t} + \beta 5\ High_FU_{f,t} \times CR_{f,t} + c\ \boldsymbol{M}_{f,t} + \epsilon_{f,t}, \quad (2)$$

where $FF5\ Alpha_{f,t+1}$ is the Fama and French (2016) five-factor (FF5) alpha based on the gross return of fund *f* in month *t+1*; $CR_{f,t}$ is the turnover of fund *f* in month *t*; $Low_FU_{f,t}$ = 1 for overpriced funds (if FU is in the bottom tercile in month *t*); $High_FU_{f,t}$ = 1 for underpriced funds (if FU is in the top tercile in month *t*); and $\boldsymbol{M}_{f,t}$ is a vector of fund characteristics commonly used in the literature, including total net assets, expense ratio, return volatility, fund flow, and fund family size. Definitions of all variables are provided in Table A.1 of the Appendix at the end of the paper.[13]

We estimate Equation (2) with style-by-time fixed effects, to focus on variation across funds that operate within the same style categories at the same point in time. This fixed-effect structure ensures that the interactive effect between turnover and stock-picking skill that we examine is not simply driven by common time-varying investment opportunities, either at the market-wide level or within specific investment styles. We expect that greater turnover (CR) should have a stronger positive

[13] Internet Appendix Table IA.1 provides further details on the variable definitions presented in Table A.1.

relation with future performance for funds with greater skills in identifying underpriced stocks (with high FU) but a weaker positive relation, or even a negative relation, for funds with lower skills in identifying such profit opportunities (with low FU).

Results from estimating Equation (2) are reported in Panel A of Table 3. Column (1) includes the two dummy variables that identify overpriced and underpriced funds (Low FU and High FU), but excludes fund turnover (CR) as well as any interactive effects involving turnover. The coefficients of these two dummy variables indicate that overpriced funds (with low FU) slightly underperform the omitted group (i.e., the middle FU tercile) by an insignificant monthly FF5 alpha of 0.8 basis points (bps, t-ratio = -0.52), while underpriced funds (with high FU) significantly outperform the omitted group by 2.9 bps per month (t-ratio = 3.69).

Columns (2) and (3) of Panel A in Table 3 separately include the indicator variable for either Low FU or High FU funds, along with turnover itself (CR) and its interaction with that indicator variable. The coefficients of these two interaction terms (Low FU × CR and High FU × CR) reveal that the relation between turnover (CR) and performance differs dramatically for each tercile of funds with either low or high ability to identify underpriced securities, relative to all other funds. In particular, in column (2) the coefficient of (Low FU × CR) is -0.625 (t-ratio = -3.27), while in column (3) the coefficient of (High FU × CR) is +0.603 (t-ratio = 3.28). This evidence indicates that, for *overpriced funds* (with low FU) higher turnover (CR) significantly *reduces* performance, while for *underpriced funds* (with high FU) higher turnover (CR) significantly *improves* performance, when either subset is compared with all other funds in the remaining two terciles.

This evidence is corroborated in column (4) of Panel A in Table 3, when we include both indicators (High FU and Low FU), and their respective interactions with turnover. This result confirms that higher turnover significantly reduces performance for funds with low FU, but significantly enhances performance for funds with high FU, relative to funds in the middle FU tercile.

The economic significance of these results can be determined by considering the influence of a one-standard-deviation change in turnover (CR) for the subsets of funds with either low or high FU.

For this exercise, Table 1 indicates that a one-standard-deviation change in fund turnover is 4.60%. Thus, a one-standard-deviation increase in turnover is associated with a *decrease* in fund performance of -2.875 (4.60 × -0.625) bps per month (or -34.5 bps per year) for the subset of funds with *overpriced* stocks (Low FU), but with an *increase* in fund performance of 2.774 (4.60 × 0.603) bps per month (or 33.3 bps per year) for the subset of funds with *underpriced* stocks (High FU), when either subset is compared with all other funds. This evidence establishes that greater turnover is significantly *more harmful* for funds with a weak ability to identify underpriced securities, but significantly *more profitable* for funds where such skills are strong, when either subset is compared to all other funds.

We note that the unconditional relation between turnover and performance for the tercile of underpriced funds (with high FU), by itself, is positive and highly significant, while the analogous unconditional relation for the tercile of overpriced funds (with low FU) is negative but insignificant. This outcome is revealed by the sum of coefficients for CR and each interaction term in columns (2) to (4) of Panel A in Table 3, respectively (i.e., CR + Low FU×CR or CR + High FU×CR).[14]

3.2 Alternative, Parsimonious Specification

In this subsection, we specify a more parsimonious model which replaces our two indicator variables in Equation (2) that identify terciles of funds with high or low levels of skill in identifying undervalued stocks (Low FU and High FU) with the continuous measure (FU) itself. We then estimate the following model that includes FU, CR, and their interaction (FU × CR), as follows:

$$FF5\ Alpha_{f,t+1} = \alpha^0 + \beta\ FU_{f,t} + \gamma\ CR_{f,t} + \delta\ FU_{f,t} \times CR_{f,t} + c\ \boldsymbol{M}_{f,t} + \epsilon_{f,t}\,. \quad (3)$$

All other aspects of Equation (3) such as controls, fixed effects, and clustering of standard errors are the same as in Equation (2). The results for Equation (2) from Panel A of Table 3 indicate a stronger positive relation between turnover (CR) and performance for funds with more underpriced stocks

[14] For example, the F-test in column (3) or (4) of Panel A in Table 3 indicates that the sum of coefficients for CR and High FU×CR is either 0.730 or 0.732, which is significantly greater than zero. This outcome establishes that, for the tercile of underpriced funds (with high FU), higher turnover is associated with a large and significant increase in performance. In contrast, the F-test in column (2) or (4) indicates that the sum of coefficients for CR and Low FU×CR is -0.092 or -0.095, which is not significantly different from zero. This outcome indicates that, for the tercile of overpriced funds (with low FU), higher turnover is associated with a decline in performance that is relatively small and insignificant.

(when FU is higher), but a weaker positive or even negative relation for funds with more overpriced stocks (when FU is lower). Thus, we expect the coefficient of the single interaction term (FU × CR) in Equation (3) to be positive, which would corroborate a *stronger positive* relation between turnover (CR) and performance for funds with *higher FU* (i.e., higher ability to identify underpriced assets), which switches to a *weaker positive or even negative* relation between CR and performance for funds with *higher* FU. We present the results for this parsimonious model in Equation (3) for all remaining tests.[15]

Results from estimating Equation (3) are provided in Panel B of Table 3. First consider the evidence in columns (1) and (2), when we exclude the interaction term, FU × CR. The coefficient on FU alone in column (1) changes little in column (2), after controlling for turnover (CR), and it remains significantly positive (t-ratio = 2.47), while the coefficient on turnover (CR) is also positive and significant (t-ratio = 3.39) in column (2). Furthermore, the coefficient on CR is economically significant, since a one-standard-deviation increase in CR is associated with a higher FF5 alpha of 1.56 (4.60 × 0.340) bps per month (or 18.8 bps per year). Together, these results indicate that funds with greater skill at either identifying underpriced stocks (higher FU) or at trading in these stocks (higher CR) have significantly higher subsequent risk-adjusted returns.

Most importantly, column (3) of Panel B in Table 3 indicates that the coefficient of (FU × CR) is significantly positive (i.e., $\delta = 0.068$, t-ratio = 2.93). This outcome corroborates our main result from Panel A that the relation between turnover (CR) and performance depends on a fund's ability to identify undervalued stocks (FU). In particular, from Equation (3) the marginal effect of turnover (CR) on performance can be expressed as ∂(FF5 Alpha) / ∂ CR = $\gamma + \delta \times$ FU (= -3.739 + 0.068 × FU). This relation indicates that turnover (CR) has little or no impact on performance when FU = 55, which is roughly halfway between 0 and 100.[16] In contrast, greater turnover is more beneficial when funds hold more *undervalued* stocks (i.e., when FU > 55) while it is less beneficial, or even harmful, when funds

[15] The remaining tests produce similar results and conclusions when we instead estimate Equation (2).
[16] In particular, ∂(FF5 Alpha) / ∂ CR = -3.739 + 0.068 × FU = 0 when FU = 55.

hold more *overvalued* stocks (i.e., when FU < 55). These results help to reconcile the mixed evidence from prior research by establishing that the nature and strength of the relation between fund turnover and performance is highly dependent on the fund's ability to identify profit opportunities (FU).

3.3 Decomposing Total Fund Turnover into Buy-Side and Sell-Side Turnover

We next examine more closely the mechanism behind our main result that the relation between fund turnover and performance depends on our FU measure, by decomposing total fund turnover (CR) into its buy-side (CR_Buy) and sell-side (CR_Sell) components. If higher FU correctly identifies funds that are more skilled at identifying undervalued stocks, then we would expect these funds with higher FU to exploit this skill through *buying* activity, either by initiating new positions in undervalued securities or by adding to undervalued securities already present in the portfolio. In contrast, it is more difficult for funds to exploit such opportunities effectively through *selling*.

Alternatively, it is possible that a high value of FU could simply reflect a more general form of skill, which a fund might exploit through more active trading in general, regardless of whether the trading happens on the buy or sell side. These two possibilities generate different predictions. If FU captures skill in identifying undervalued stocks, then we would expect FU to positively interact with the fund's buying activity (CR_Buy), but perhaps not as much with selling activity (CR_Sell). In contrast, if FU reflects a more general aspect of managerial skill, then FU could positively interact with both CR_Buy and CR_Sell to enhance performance.

Table 4 reports analysis of an expanded version of Equation (3) that includes FU along with CR_Buy and CR_Sell separately in columns (1) and (2), as well as together in column (3). Throughout this Table, the coefficient of the first interaction term (FU × CR_Buy) is positive and significant, while the coefficient of the second interaction term (FU × CR_Sell) is insignificant. This outcome implies that the conditional profitability of turnover documented above in Table 3 is predominantly driven by buy-side trading activity. This evidence is consistent with the first interpretation presented above, suggesting that funds with a greater ability to identify underpriced assets are able to exploit such mispricing opportunities mainly through buying, rather than selling.

3.4 Alternative Fixed-Effect Structures

By employing style-by-time fixed effects, our investigation exploits variation in both the ability to identify profit opportunities (FU) and trading activity (CR) across funds that operate within the same style categories at the same point in time. In Table 5, we re-estimate Equation (3) and its variant that decomposes total turnover into buy-side and sell-side activity using different fixed-effect structures. In columns (1) and (2), we employ separate style and time fixed effects (non-interacted). We then use fund fixed effects only in columns (3) and (4), and both fund and time fixed effects separately in columns (5) and (6).

Columns (1), (3), and (5) in Table 5 establish that the coefficient of (FU × CR) remains positive and significant under all three alternative fixed-effect structures. Moreover, columns (2), (4), and (6) confirm that this conditional profitability of turnover is driven by buy-side trading more than sell-side activity. In particular, the coefficient of (FU × CR_Buy) is two to three times larger in magnitude than the coefficient of (FU × CR_Sell) in these latter three columns, although there is some evidence of a significant interactive effect for CR_Sell, especially with fund fixed effects only in column (4).

Importantly, the positive interactive effect of fund underpricing (FU) on the relation between fund turnover (CR) and performance persists when we employ these alternative fund and time fixed effects separately, as shown in columns (5) and (6) of Table 5. With separate fund and time fixed effects, the positive coefficient of FU × CR is estimated from *within-fund* changes in FU and turnover over time, after removing common time-series variation. This outcome means that, for the same fund and in the same market-wide opportunity regime, higher turnover is associated with better future performance during periods when the fund holds more undervalued stocks (higher FU). Thus, the conditional profitability of turnover is not only driven by cross-fund differences or by market-wide or style-wide time-varying investment opportunities, but also by within-fund variation over time in the extent to which a fund's portfolio reflects the successful identification of underpriced stocks.

This within-fund variation in FU has a different interpretation from the analogous cross-fund variation exploited so far in the analysis (i.e., when style by time fixed effects are used). Even if a

fund's underlying ability to identify profit opportunities is relatively stable over time, FU can change because the extent to which this ability is reflected in the fund's portfolio will vary over time. This time-variation in FU could occur because funds may rely more on firm-level signals (stock-picking) at some times, while relying on macro signals (timing) at other times. Thus, the same fund's portfolio may reflect stock-level mispricing more strongly during some periods than others, which would lead to such time variation in FU.[17] Another potential source of time-variation in FU is non-information-driven trading caused by fund flows or liquidity needs (e.g., Edelen, 1999), portfolio window-dressing (e.g., Agarwal, Gay, and Ling, 2014), or tax considerations (Poterba and Weisbenner, 2001). Such non-information-based trading can dilute the portfolio's exposure to successfully identified mispricing opportunities, resulting in lower FU at certain times.

4. Potential Alternative Explanations for Our Main Results

4.1 Luck versus Persistent Skill in Identifying Undervalued Stocks

A high level of fund underpricing in any month could arise due to luck or random (noise) trading, rather than innate ability to identify underpriced stocks. Alternatively, if some fund managers are truly capable of identifying underpriced assets, then we should observe persistence in this skill over time for some funds. We address this issue by examining whether funds that display high fund underpricing (FU) ranks in some periods preserve those ranks in subsequent periods.

Panels A to C of Internet Appendix Table IA.3 present three transition matrices that report the percentage of funds that are ranked in the highest, middle, or lowest FU deciles (D10, D5, or D1) during any given month (*t*), which remain in the same decile over the next 12 months. First consider the subset of funds in Panel A that are initially ranked in the highest FU decile (D10) in month (*t*). These underpriced funds display strong persistence in the ability to identify underpriced assets, with 80.10% remaining in the high FU decile (D10) after one month, 70.88% remaining in the same decile (D10) two months later, and so on. In fact, 42.53% of these funds remain in the same high FU decile

[17] See Kacperczyk, van Nieuwerburgh, and Veldkamp (2014, hereafter KVV). Consistent with this interpretation, in Table IA.2 we exploit within-fund variation and show that FU is positively associated with KVV's stock-picking measure, but negatively associated with their market-timing measure. This evidence suggests that time variation in FU within a fund reflects, at least in part, variation in the extent to which the fund relies on its stock picking ability.

even after 12 months. Furthermore, 92.61% of these funds ranked in the top FU decile in month (*t*) remain in the top *two* deciles after one month, while 87.16% remain in D9 or D10 after two months, and so forth, with 60.79% remaining in D1 or D2 even after twelve months. This evidence indicates a highly persistent ability of skilled managers with the most underpriced funds in any given month to continue to maintain portfolios with the most underpriced stocks at least twelve months later.

Next consider the lowest skill funds in any given month (*t*) that are initially ranked in the lowest FU decile (D1), in Panel C of Internet Appendix Table IA.3. These overpriced funds in month (*t*) are also persistent, with a 78.09% probability of remaining in the same FU decile (D1) one month later, while 68.83% of these funds remain in the same low FU decile two months later, and so on. In fact, 41% of these funds remain in the same low FU decile even after 12 months.

In contrast, Panel B of Internet Appendix Table IA.3 documents that funds with medium skill in the middle decile by FU (D5) in any month (*t*) are considerably less persistent. Only 48.26% of these D5 funds remain in the same decile after one month, and this proportion declines to just 15.85% after 12 months. Instead, these medium-skilled funds are more likely to disperse toward the neighboring FU deciles, D3 to D7. These findings indicate that extreme levels of fund underpricing (FU) are highly persistent, whereas moderate fund underpricing is more transitory.

Together, this evidence supports the view that high values for a fund's FU indicate a persistent innate ability of some skilled fund managers to identify and maintain portfolios with underpriced assets. This persistence in high FU for some funds is less consistent with the view that these managers are simply lucky in picking undervalued stocks during some months.

4.2 Placebo Test – Fund Underpricing, Turnover, and Performance for Index Funds

It is also possible that our main results are spurious, perhaps due to methodological choices. We address this concern by implementing a placebo test on the sample of index funds. Since index fund managers passively replicate a benchmark portfolio, our proxy for a fund manager's ability to identify underpriced assets (FU) should not reflect persistent skill in stock selection for these funds. Still, it is possible that index funds could gain passive exposure to underpriced or overpriced stocks

due to changes in benchmark composition or fluctuations in stock valuations over time, which may conceivably predict performance even in the absence of active security selection.

On the other hand, by design, index fund managers do not attempt to identify or exploit profit opportunities through active *trading* in underpriced securities as they passively replicate a benchmark portfolio. Thus, index fund turnover (CR) by itself should not be associated with fund performance. More importantly, any variation in FU across the sample of index funds should not affect the association between turnover (CR) and performance. That is, the interaction of our proxy with turnover (FU × CR) should not significantly predict the performance of index funds, which by their nature do not attempt to either identify or exploit such undervalued stocks through *trading*. In this light, re-estimating Equation (3) for the sample of index funds should observe no significant interaction between FU and turnover (FU × CR) in explaining future fund performance.

We present the results of this placebo test in Table 6. Panels A and B replicate the analysis from Table 3 for the sample of index funds, while Panel C partitions total index fund turnover into buy-side and sell-side turnover. As expected, this analysis reveals no significant interactive effects between the ability to identify underpriced assets and turnover (FU × CR) in explaining future performance. In Panel A, the coefficients of the two dummy variables (Low FU and High FU) are insignificant, as are the coefficients of CR and the interaction terms (Low FU × CR and High FU × CR). In Panel B, the coefficient of FU by itself is significantly greater than zero, indicating that the observed variation in FU across the sample of index funds is positively associated with performance. However, once again the coefficients of both CR and the interaction term (FU × CR) are insignificant, as expected. Finally, Panel C further indicates that the interactions involving FU and both buy-side and sell-side turnover (i.e., FU × CR_Buy and FU × CR_Sell) are also insignificant.

The most important outcome from this placebo test is that all interaction terms involving fund underpricing (FU) and turnover (CR) throughout Table 6 are insignificant. Thus, it is unlikely that our main results for non-index funds in Tables 3 - 5 are spurious. This analysis provides further

corroboration for our conclusions regarding differences in the relation between fund turnover (CR) and performance across subsets of mutual funds with different abilities to identify underpriced assets.

4.3 Underpricing, Turnover, and Performance for Funds with Large Inflows or Outflows

The open-ended structure of mutual funds results in substantial trading activity induced by fund flows, which is often unrelated to the information that active fund managers attempt to exploit (Edelen, 1999). For example, Table 2 documents that the decile of funds with high FU experiences significantly higher inflows compared to funds with low FU. This behavior raises the potential concern that our main results (i.e., the FU × CR effect) may be driven by trading induced by large fund inflows or outflows. For example, big inflows into high-FU funds could compel buying that might exert temporary upward price pressure on the underlying securities purchased by these funds, especially if inflows and the resulting compelled purchases are correlated across funds in the same style category.

We examine this possibility by adding to Equation (3) two indicator variables for fund-month observations with either large outflows or inflows, which we interact with our main variables (FU, CR, and FU × CR). The Big Outflow (Big Inflow) indicator variable equals one for fund-month observations with large outflows (inflows) that are above the median value of fund outflows (inflows), measured across all funds that operate in the same style category during month (t), and zero otherwise.

The evidence is reported in Table 7. The third row reveals that the coefficient of our main interaction term (FU × CR) remains positive and significant in both columns of Table 7, when we include dummy variables for either big inflows or big outflows. This outcome indicates that fund underpricing (FU) drives the divergent relation between fund turnover (CR) and performance for the omitted group of mutual funds that do not experience either large inflows or large outflows during month (t). Furthermore, in contrast to this main result for the omitted group, none of the other interaction terms in Table 7 between the indicator variables (Big Inflow or Big Outflow) and our main

variables of interest (FU, CR, or FU × CR) are significant. Most importantly, the coefficients of the triple interaction terms, Big Outflow × FU × CR and Big Inflow × FU × CR, are also insignificant.[18]

These findings indicate that the positive interactive effect between FU and turnover (FU × CR) in explaining fund performance that we document for the omitted group of funds, with no major fund flows, does not change significantly when funds experience either large inflows or large outflows. This evidence implies that the significant interactive effect between FU and CR in explaining future fund performance is not driven by the flow-induced trading of mutual funds.

4.4 Fund Turnover, Fund Mispricing, and Longer-Term Performance

Although flow-induced trading does not explain our key findings, aggressive purchases by funds with greater skills in identifying underpriced assets (FU) may create temporary price pressure for these holdings, leading to temporarily higher returns that later reverse. We address this possibility by examining whether the conditional profitability of turnover documented in Table 3 extends beyond one month (t+1), by estimating Equation (3) over future three-month periods up to 12 months later.

The results are reported in Table 8, and document that the significant positive coefficient on (FU × CR) is most pronounced in the short-term extending up to three months later. Over later horizons, this effect decays in magnitude and significance without becoming significantly negative. This outcome establishes that the enhanced performance associated with higher turnover for funds with greater skill in identifying underpriced opportunities (higher FU) does not reflect temporary price pressure which subsequently reverses over the next twelve months. This evidence also suggests that funds with higher FU are able to identify and exploit undervalued stocks before their prices fully adjust. Together, this analysis helps to rule out the possibility that aggressive purchases by funds with greater skills in identifying underpriced opportunities (FU) may simply create temporary price pressure for these holdings in the following month.[19]

[18] Our main results (i.e., the significant positive coefficient of FU × CR) are also robust when we define the Big Outflow and Big Inflow dummy variables using the top and bottom terciles or quintiles by inflows and outflows.

[19] In untabulated results (available upon request), we find that the coefficient of FU x CR remains positive and insignificant at the .05 level over subsequent three-month periods further in the future, up to 24 months later.

5. Additional Analysis: Evidence from Periods of Market Stress

PST (2017) show that funds trade more aggressively and more profitably when market dislocations are likely to be greater, during periods of high investor sentiment, market volatility, or illiquidity. However, this time-series effect cannot by itself explain our baseline results, because our specifications include style-by-time fixed effects which control for market-wide or style-wide profit opportunities available to all funds operating within a given style, at a given point in time. Nonetheless, periods with elevated levels of market sentiment, volatility, or illiquidity might conceivably give rise to greater mispricing opportunities, which could magnify cross-sectional differences in the profitability of turnover between funds with stronger versus weaker opportunity-identification skills. During such periods of elevated mispricing, funds with higher FU might be better able to distinguish genuine opportunities from noise, while funds with lower FU may be more likely to mistakenly identify poor opportunities as genuine opportunities.

In this subsection, we create indicator variables for periods of high overall market sentiment, volatility, or illiquidity (all labeled 'High') that identify the subsets of months in our sample that are above the median based on either the investor sentiment index of Baker and Wurgler (2006), the standard deviation of returns on the market portfolio including all stocks in the CRSP universe, or the market-wide illiquidity measure of Pástor and Stambaugh (2003). We then augment Equation (3) to include additional interaction terms between each of these three indicator variables and our main variables of interest (FU, CR, and FU × CR).[20]

Results are reported in Table 9. First consider the evidence for periods of high sentiment or volatility in columns (1) to (4). The coefficient of the double interaction term (CR × High) in columns (1) and (3), and the triple interaction term (FU × CR × High) in columns (2) and (4), are all significantly positive. These results establish that, during periods of high investor sentiment or market volatility, the relation between turnover and performance becomes significantly more positive for funds with greater

[20] These results are similar when we identify periods of high market sentiment, volatility, or illiquidity using observations in the highest tercile or quintile by each measure, rather than above the median (results are available upon request).

skill in identifying profit opportunities (i.e., with higher FU). This evidence suggests that periods with greater mispricing opportunities associated with greater market-wide sentiment or volatility tend to amplify the differences in the relation between fund turnover (CR) and profitability across funds with divergent abilities to identify such profit opportunities (FU). In fact, the smaller coefficients for FU × CR (which capture the interaction effect in the omitted periods with lower sentiment or volatility) suggest that the positive interactive effect is mainly concentrated during periods of elevated sentiment and volatility.

Next consider the evidence for periods of high market illiquidity presented in columns (5) and (6) of Table 9. We do not find a similar significant interactive effect when we proxy for periods of elevated market-wide mispricing opportunities using the aggregate measure of illiquidity from Pástor and Stambaugh (2003). One possible explanation for the insignificant coefficients on (CR × High) and (FU × CR × High) in columns (5) and (6) is that, although periods with greater illiquidity may provide more mispricing opportunities, trading costs might be elevated under these conditions and limit the extent to which any such opportunities could be exploited through trading.

These results support and extend our key finding that the relation between turnover (CR) and performance depends on a fund's ability to identify profit opportunities (FU). PST (2017) focus on how time-varying market conditions affect the typical relation between a fund's turnover and performance over time. In contrast, this evidence shows that conditions of high market sentiment or volatility primarily magnify the cross-sectional differences in the profitability of fund turnover across funds with stronger versus weaker ability to identify underpriced securities (FU). Thus, we extend the key finding in PST (2017) that periods associated with greater pricing dislocations increase the overall profitability of fund trading, on average, by showing that such periods also amplify the extent to which the relation between a fund's turnover and performance depends on its ability to identify profit opportunities.

6. Robustness of Our Main Results

6.1 Alternative Measures of Fund Performance

In this subsection, we explore the robustness of our main results with respect to the following alternative measures of fund performance: monthly gross return (adding back expenses); CAPM alpha; Carhart (1997) four-factor (FF4) alpha; alpha of a liquidity factor model (FFL) that includes the Carhart (1997) four factors plus the liquidity factor of Pástor and Stambaugh (2003), and alpha of a mispricing factor model (FFM) that includes the Carhart (1997) four factors plus a mispricing factor based on Stambaugh and Yuan (2017),[21] where all alpha measures are estimated using the fund's monthly gross returns. Here we re-estimate Equation (3) using these alternative performance measures.

The results are provided in Internet Appendix Table IA.4, and show that the coefficient of our key interaction term (FU × CR) remains positive and significant regardless of the performance measure used to estimate Equation (3). These findings indicate that our main results regarding the conditional profitability of turnover do not depend on the method used to measure risk-adjusted performance. Moreover, the robustness of this interactive effect suggests that our main results are not driven by possible differences in exposures to common risk factors across funds. Importantly, the coefficient of the key interaction (FU × CR) remains significant even after we control for systematic exposure to the Stambaugh and Yuan (2017) mispricing factor, which is based on their 11 anomalies. This outcome suggests that the conditional profitability of turnover extends beyond the returns associated with systematic exposure to the anomaly-based mispricing premium, which is consistent with managers possessing opportunity identification skills that extend beyond strategies that rely on passive exposure to a mispricing-factor.

6.2 Alternative Measures of Fund Skill, Portfolio Liquidity, Activeness, and Mispricing

In this subsection, we examine whether our main result (i.e., the significant positive coefficient of the interaction term, FU × CR) remains significant when we control for alternative fund

[21] Following Stambaugh and Yuan (2017), the mispricing factor is constructed as the return spread between portfolios of underpriced and overpriced stocks, averaged across size groups. Stocks are classified as underpriced or overpriced based on a composite mispricing measure obtained by averaging their rankings across the 11 anomalies examined by Stambaugh and Yuan (2017).

characteristics related to managerial skill, portfolio liquidity, fund activeness, and fund mispricing. First, following PST (2017), we consider the expense ratio (labeled Exp_Ratio) as an alternative proxy for overall managerial skill. Second, following Cohen, Coval, and Pástor (2005) and Shen, Tong, and Yao (2021), we consider past fund performance as another proxy for managerial skill.[22] Third, we analyze the portfolio liquidity measure of PST (2020, labeled L), who show that the relation between turnover and performance is stronger for funds with less-liquid portfolios.[23] The idea is that higher trading costs make trading worthwhile only when managers perceive sufficiently profitable investment opportunities. Third, we employ two measures of fund activeness. The first is the Active Weight measure from Doshi, Elkamhi, and Simutin (2015, labeled AF1), defined as one half of the sum of the absolute differences between the market-capitalization weight and the actual weight for each stock held by the fund. The second is the Active Share measure of Cremers and Petajisto (2009, labeled AF2), which instead is computed as one half of the sum of the absolute deviations between each stock's actual weight in the fund versus the stock's weight in the fund's own benchmark portfolio.[24]

We also propose two additional measures that capture managerial activeness combined with mispricing of the underlying fund holdings. The first such measure is called 'active fund overpricing' (labeled AFO1), defined as one half of the weighted sum of the mispricing scores (MISP) of the fund's individual stockholdings, where the weights are the deviations between every stock's market-capitalization weight in the fund versus the fund's actual weight in that stock. The second such measure (labeled AFO2) is the 'active fund overpricing' measure of Avramov et al. (2020), defined as one half of the weighted sum of the mispricing scores (MISP) of the fund's stockholdings, where the weights are the deviations between the weight of every stock in the fund's benchmark portfolio and the actual weight of that stock in the fund.[25]

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[22] Past fund performance is constructed as the average FF5 alpha over the last 12 months. Results are similar when we use the cumulative FF5 alpha.

[23] Specifically, L is constructed as the inverse of the sum of squared portfolio weights scaled by the corresponding stocks' market-cap weights, with a higher L indicating higher portfolio liquidity.

[24] We first generate nine potential benchmark portfolios to match with each fund by double-sorting all stocks every month (t) based on firm size and book-to-market. We then compute the Active Share of the fund with respect to each of the nine benchmark portfolios, and select the benchmark that generates the lowest active share (Cremers and Petajisto, 2009).

[25] The benchmark portfolios used to construct AFO2 for each fund are the same as the benchmarks used in AF2.

The results of this analysis are provided in Table 10. In Panel A, we begin by *replacing* our own proxy for fund managers' ability to identify underpriced stocks (FU) in Equation (3) with each of these six alternative measures, respectively. The first fourteen columns in Panel A analyze each alternative measure separately, while the fifteenth column examines all seven measures together. First consider the standalone coefficients for these seven measures in columns (1) – (7) of Panel A, when we exclude fund turnover (CR) from the model. In columns (1), (2) and (4), the coefficients of the three alternative measures, Exp_Ratio, Past_FF5, and AF1, are positive and significant indicating that these three measures of fund skill and activeness are positively related to future performance, when examined by themselves. In contrast, in columns (3), (5), (6), and (7) the coefficients of the remaining measures (L, AF2, AFO1, and AFO2) are insignificant.[26]

Next consider columns (8) – (14) in Panel A of Table 10, when we add turnover (CR) back to the model, along with its interaction with each alternative measure separately. The interaction terms involving the first five measures (i.e., Exp_Ratio × CR, Past_FF5 × CR, L × CR, AF1 × CR, and AF2 × CR) in columns (8) – (12) are all insignificant at conventional levels. As expected, the coefficients of four of these interaction terms are positive (i.e., Exp_Ratio × CR, Past_FF5 × CR, AF1 × CR, and AF2 × CR), while the coefficient of L × CR is negative. This evidence suggests that these five measures all tend to have the expected association with the profitability of fund turnover (i.e., the impact of CR on performance), but this association is not statistically significant. In contrast, the analogous interaction terms for the last two measures of active fund overpricing (AFO1 × CR and AFO2 × CR) in columns (13) and (14) are significantly negative, indicating that these measures of active fund *over*pricing are negatively related to the profitability of turnover (CR), as expected. This latter outcome is again consistent with the evidence in Avramov et al. (2020), and indicates that greater active trading by mutual funds in *over*priced stocks results in worse performance, also as expected. Finally, the last column of Panel A includes all seven alternative measures, along with their respective interactions with

[26] Note that the latter two proxies for 'active fund *over*pricing' (AFO1 and AFO2) rely on MISP itself, where larger values indicate funds that are more *over*priced. In contrast, our proxy (FU) relies on (100 – MISP), so larger values of FU indicate funds that are more *under*priced. In this light, a negative coefficient for AFO1 or AFO2 indicates that more *over*priced funds tend to perform *worse* (or more *under*priced funds tend to perform *better*), as expected.

CR. With the exception of the interactions involving CR with AF2, the interactions of CR with the other five measures preserve the sign of the coefficients documented in columns (8) – (14). Moreover, none of the coefficients of the interaction term remain statistically significant. Together, the evidence in Panel A suggests that these alternative measures and their respective interactions with turnover tend to be somewhat effective in predicting performance, as well as influencing the relation between turnover and performance. However, these respective relations are not consistent or robust when we exclude our own proposed measure of fund underpricing (i.e., FU and FU × CR) from the analysis.

Finally, consider the results in Panel B of Table 10, when we *augment* Equation (3) to include each alternative measure and its interaction with turnover, along with our own main variables of interest (CR, FU, and FU × CR). First consider the interactive effects between fund turnover (CR) and each of these seven alternative measures examined separately, in columns (1) to (7) of Panel B. In columns (1), (4), and (5), the coefficients of these interaction terms are again positive but insignificant at conventional levels. These results indicate that the expense ratio and the first two measures of fund activeness (AF1 and AF2) interact mildly but insignificantly with turnover in predicting performance, when we control for our own proxy for fund underpricing (FU), similar to the evidence in Panel A. In column (3), the coefficient of the interaction term, L × CR, is negative as expected, but it is now significant at the 10% level. Likewise, now in columns (6) and (7) the coefficients of the analogous interaction terms involving AFO1 and AFO2 are negative but insignificant, indicating a mild but insignificant interaction with turnover. Once again, the last column of Panel B is generally consistent with the evidence in columns (1) – (7) when we include all seven alternative measures together, along with their respective interactions with CR.

The most important result appears in the third row of Panel B in Table 10, which establishes that inclusion of these seven alternative measures and their respective interactions with fund turnover does not alter our main result, the significant positive coefficient on (FU × CR).[27] This evidence

[27] In unreported analysis, we also consider past performance as an alternative proxy for fund skill, following Shen, Tong, and Yao (2021). Similar to their findings, past performance also interacts positively with CR to predict fund performance. However, this interaction becomes insignificant when we include the interactions of CR with FU and the other measures considered above, while our main result (i.e., the significant coefficient of FU × CR) remains positive and significant.

indicates that the interactive effect of our own proxy for fund skill with turnover (FU × CR) on performance is stronger and more consistent than the interaction between CR and each of these seven alternative measures of fund skill, portfolio liquidity, activeness, and overpricing. Together, these results establish that our proxy for the ability of fund managers to identify underpriced stocks (FU) has a stronger and more stable impact on the predictive relation between turnover (CR) and fund performance, when compared to these alternative measures of fund skill.

7. Conclusions

We build upon previous research that studies the relation between the portfolio turnover of mutual funds and their future performance, by examining whether the profitability of mutual fund trading activity depends on the fund's ability to identify and hold underpriced securities. We operationalize this investigation by distinguishing between the ability of mutual funds to *identify* profit opportunities and the intensity with which they trade to *exploit* such perceived opportunities. We accomplish this task by introducing a new measure of a fund's ability to identify profit opportunities. Our measure calibrates the extent to which a fund's quarterly holdings are underpriced or overpriced according to the monthly mispricing metrics for individual stocks held by the fund, based on the work of Stambaugh, Yu, and Yuan (2015). We document that the relation between fund turnover and future performance depends critically on our measure for a fund's ability to identify undervalued stocks.

Our main result is that higher fund turnover is associated with better performance for the tercile of funds that are most skilled at identifying profit opportunities (with high FU), but worse performance for the tercile of funds that are least skilled (with low FU), when each group is compared to all the other funds. This evidence implies that active trading by mutual funds does not uniformly improve performance across all funds. Instead, more active trading enhances performance when it is guided by the successful identification of profit opportunities. This evidence of heterogeneity in the ability of funds to identify profit opportunities, and its impact on the relation between fund turnover and performance, helps to explain the mixed results in prior research that attempts to uncover the overall relation between turnover and performance. It also provides a framework for understanding the

previously documented heterogeneity in the empirical relation between turnover and performance. To the best of our knowledge, this is the first study to propose a direct measure of fund managers' ability to identify underpriced securities, and establish that the relation between fund turnover and future performance is conditional on this ability.

We further show that this conditional relation between fund turnover and performance materializes primarily through buy-side trading activity. This outcome is consistent with the expectation that funds with greater ability to identify undervalued stocks should be able to exploit such opportunities primarily by increasing exposure to these securities through buying, rather than selling.

Our main findings are robust to alternative fixed-effect structures, alternative measures of fund performance, and alternative measures of fund managerial skill, liquidity, activeness, and mispricing, and they are not driven by large fund inflows or outflows. Importantly, the interaction between a fund's ability to identify underpriced securities and turnover remains a significant predictor of future fund performance even after controlling for these alternative measures, as well as their respective interactions with turnover. Furthermore, our main findings survive when we focus on within-fund variation through time, which suggests that the relation between turnover and performance is not only driven by cross-sectional differences in funds' abilities to identify profit opportunities. Instead, this relation is also affected by within-fund variation in the manifestation of such managerial skills that arise because a fund's exposure to successfully identified profit opportunities can change through time.

Finally, this analysis extends and complements the work of PST (2017), who document a positive within-fund relation between turnover and performance over time, while interpreting fund turnover as an endogenous response to time-varying investment opportunities. Specifically, we show that the profitability of turnover does not arise simply due to time-varying profit opportunities, but also due to cross-sectional differences in the abilities of different funds to identify such opportunities at any given point in time. Moreover, we also show that funds with greater ability to identify profit opportunities are able to benefit disproportionately more from active trading during periods with greater mispricing opportunities, characterized by elevated investor sentiment or market volatility.

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Appendix

Table A.1. Variable Definitions[28]

TNA = Fund Total Net Assets	Fund total net assets (TNA) is obtained from CRSP Mutual Fund Database (MFDB). CRSP measures TNA as total assets minus total liabilities at month-end. Reported in millions of dollars.
Family_Size = Fund Family Size	Total TNA of all funds within the fund's family at month-end. Reported in millions of dollars.
RET_t = Fund Net Return in Month *t*	Monthly net return for each mutual fund share class is obtained from CRSP Mutual Fund Database (MFDB). CRSP calculates monthly net return as the percentage change in net asset value, inclusive of dividend and capital gains distributions, and net of total expenses, following the definition in the CRSP Survivor-Bias-Free US Mutual Fund Database (MFDB) Guide (2023, p. 9). For funds with multiple share classes, we compute fund-level net returns by the TNA-weighted average across all share classes. The weights are based on the previous month's total net assets of each share class in the same fund.
$RRET_t$ = Fund Gross Return in Month *t*	Monthly fund-level gross return for each mutual fund share class is calculated as the sum of fund-level monthly net returns and 1/12 of the annual expense ratio.
$HRET_t$ = Fund Holdings Return in Month *t*	Monthly holdings return for each mutual fund *f* in month *t* is defined as the total return of a hypothetical buy-and-hold portfolio formed from the stock positions reported at the most recent disclosure date at time $t - \tau$ (Kacperczyk, Sialm, and Zheng, 2008).
CAPM = CAPM Alpha	For each fund, we estimate monthly alpha from the CAPM model. First, in each month *t*, we estimate a rolling regression of fund excess return on the market excess return using the previous 36 months. The regression coefficient ($\hat{b}_{f,t-1}$) captures the fund's exposure to the market factor over the previous 36 months. Second, our estimate of the fund's monthly alpha in month *t* is the realized return not explained by lagged factor exposures: $\hat{\alpha}_{f,t}^{CAPM} = R_{f,t} - RF_t - \left[\hat{b}_{f,t-1}(\mathrm{MKT}_t - RF_t)\right]$ (see Ben-David et al., 2022; Irvine, Kim, and Ren, 2024).
FF4 = FF4 Alpha	We calculate alpha using the same procedure as for CAPM alpha, replacing the market factor with the four factors in Carhart (1997).
FF5 = FF5 Alpha	We calculate alpha using the same procedure as for CAPM alpha, replacing the market factor with the five factors in Fama and French (2016).
FFL = FFL Alpha	We calculate alpha using the same procedure as for CAPM alpha, replacing the market factor with the four factors in Carhart (1997) plus the liquidity factor of Pástor and Stambaugh (2003).
FFM = FFM Alpha	We calculate alpha using the same procedure as for CAPM alpha, replacing the market factor with the four factors in Carhart (1997) plus the mispricing factor of Stambaugh and Yuan (2017).
Past_FF5 = Past FF5 Alpha	We compute Past FF5 Alpha as the average FF5 over the last 12 months.

[28] Internet Appendix Table IA.1 provides more detailed definitions of these variables.

Flow_Mon = Monthly Fund Flow	The fund flow of fund *f* during month *t* is calculated by taking the difference between the current month's TNA and the previous month's TNA, adjusted for the return aggregated across all share classes (weighted by TNA of each share class) in month *t*. This total is then normalized (scaled) by the fund's TNA at the end of month *t-1* to measure the fund flow for month *t*.
Exp_Ratio = Expense Ratio	The Expense Ratio for fund *f* in month *t* is the fund's expense ratio over the most recent fiscal year prior to month *t.* This expense ratio is the percentage of the fund's total investment that shareholders pay for the fund's operating expenses.
Std_Ret = Return Volatility	Standard deviation of monthly fund returns over the previous 24 months (*t-24* through *t-1*).
FO = Monthly Fund Overpricing	The fund overpricing (FO) measure for fund *f* in month *t* is the weighted average of the firm-specific overpricing level (MISP score of Stambaugh, Yu, and Yuan, 2015) across all stocks (*i*) held by the fund.
FU = Monthly Fund Underpricing	The fund underpricing (FU) measure for fund *f* in month *t* is computed as 100 minus the monthly fund overpricing measure.
AF1 = Fund Activeness Measure by Doshi et al. (2015)	We use the Active Weight measure in Doshi et al. (2015) as the fund activeness (AF1) measure for fund *f* in month *t*.
AF2 = Fund Activeness Measure by Cremers and Petajisto (2009)	We measure fund activeness using an Active Share measure similar to Cremers and Petajisto (2009) (AF2). They rely on fund-specific benchmark indices. Instead, we generate nine potential benchmark portfolios to match with each fund, formed by a 3×3 double sort of all CRSP common stocks on firm size and industry-adjusted book-to-market following Daniel, Grinblatt, Titman, and Wermers (1997). For each fund in each quarter, we compute the Active Share against every one of the nine potential benchmark portfolios. Each Active Share is one half of the sum of absolute differences between the fund's portfolio weight on the stock and the benchmark weight on the stock. We then select the benchmark portfolio that provides the lowest Active Share to be the benchmark of the fund, and the Active Share of that benchmark portfolio is defined as the Active Share of the fund in the quarter.
AFO1 = Monthly Fund Overpricing to Market Portfolio	The active fund overpricing measure (AFO1) is constructed in a manner similar to Avramov et al. (2020). However, rather than using each fund's individual benchmark weight for a given stock, we construct the benchmark weight as in AF1 (Doshi et al., 2015), using all stocks held by the funds and weighting them by market capitalization.
AFO2 = Monthly Fund Overpricing to Fund Benchmark Portfolio	We measure a fund's active mispricing exposure relative to its benchmark portfolio (AFO2), as follows. For every fund in each month t, AFO2 is one half of the sum of each stock's mispricing score multiplied by the difference between the fund's portfolio weight in that stock and the stock's weight in the benchmark. The benchmark is one of the nine size and industry-adjusted book-to-market portfolios that yields the fund's lowest Active Share in each quarter, held fixed for the following three months, identical to the benchmark portfolios described in the definition of AF2 above. AFO2 therefore captures the fund's mispricing tilt, net of the mispricing already embedded in the style benchmark against which the fund is most closely matched. A positive value indicates that the fund overweights overpriced stocks relative to

	funds with the same size and value orientation, while a negative value indicates the opposite.
CR = Churn Rate (Portfolio Turnover)	Fund portfolio turnover for fund *f* in month *t* is the churn rate over the most recent quarter prior to month *t* (i.e., quarter *T-1*), following Yan and Zhang (2009).
CR_Buy = Buy Portfolio Turnover	Similar to portfolio turnover, institution f 's buy portfolio turnover for quarter $T-1$ is defined as: $$CR_buy_{f,\mathrm{T}-1} \equiv \frac{Assets_buy_{f,\mathrm{T}-1}}{\sum_{i=1}^{N_f} \frac{S_{f,i,\mathrm{T}-1}P_{i,\mathrm{T}-1} + S_{f,i,\mathrm{T}-2}P_{i,\mathrm{T}-2}}{2}}$$
CR_Sell = Sell Portfolio Turnover	Similar to portfolio turnover, institution f 's sell portfolio turnover for quarter $T-1$ is defined as: $$CR_sell_{f,\mathrm{T}-1} \equiv \frac{Assets_sell_{f,\mathrm{T}-1}}{\sum_{i=1}^{N_f} \frac{S_{f,i,\mathrm{T}-1}P_{i,\mathrm{T}-1} + S_{f,i,\mathrm{T}-2}P_{i,\mathrm{T}-2}}{2}}$$
High_FU	In each month *t*, all funds within each style category are sorted into terciles by FU. High_FU = 1 if the FU for fund *f* in month *t* belongs to the highest FU tercile across all funds of the same style in month *t*; otherwise, High_FU = 0.
Low_FU	Similar to High_FU, Low_FU = 1 if the FU for fund *f* in month *t* belongs to the lowest FU tercile across all funds of the same style in month *t.*
ILLIQ= Amihud illiquidity	The Amihud (2002) illiquidity measure.
L = Portfolio liquidity	We construct portfolio liquidity following Pástor, Stambaugh, and Taylor (2020). Portfolio liquidity of fund *f* in month *t* is defined as: $$L_{f,t} = \left(\sum_{i=1}^{N_f} \frac{(w_{i,t}{}^{f})^2}{m_{i,t}} \right)^{-1},$$ where N_f is the number of stocks in fund *f*'s portfolio in the current quarter, $w_{i,t}{}^{f}$ is the fund *f*'s weight on stock *i* in month *t* and $m_{i,t}$ denotes the weight on stock *i* in month *t* in a market-cap-weighted benchmark portfolio of all CRSP stocks in the market.

Table 1. Summary Statistics

This table provides summary statistics for the main variables, for the full sample of actively managed U.S. equity mutual funds obtained from two sources, the CRSP Mutual Fund Database (MFDB) and the LSEG Mutual Fund Holdings Database (LSEG S12). We report summary statistics for several fund characteristics, and include the mean, median, standard deviation, minimum, 25th percentile, 75th percentile, and maximum. The sample period extends from 1980 through 2024.

	Mean	Median	Std Dev	Min	P25	P75	Max
Number of Distinct Mutual Funds	3,797						
Number of fund-month observations	568,528						
Number of funds per month	1,083	1,445					
Fund Portfolio Assets ($Millions)	1,516.49	263.06	6,083.46	0.00	74.59	944.54	283,380.02
TNA ($Millions)	1,736.52	298.40	7,103.42	5.00	85.01	1,076.80	306,363.10
Family Size ($Millions)	39,506.56	4,241.16	144,931.78	5.00	618.50	23,573.30	5,112,108.90
Fund Net Monthly Return	0.84%	1.23%	5.44%	−95.56%	−2.01%	3.96%	832.95%
Expense Ratio	1.15%	1.10%	0.45%	−0.51%	0.89%	1.37%	8.89%
Monthly Return Volatility	4.97%	4.79%	2.23%	0.45%	3.52%	6.05%	170.25%
Monthly Fund Flow	−0.06%	−0.48%	4.71%	−18.06%	−1.44%	0.70%	30.85%
Quarterly Fund Turnover (Churn Rate, CR)	5.22%	4.16%	4.60%	0.00%	1.86%	7.37%	61.92%
Quarterly Buy Portfolio Turnover (CR_Buy)	8.82%	6.15%	10.40%	0.00%	2.97%	11.07%	196.13%
Quarterly Sell Portfolio Turnover (CR_Sell)	11.12%	7.72%	13.17%	0.00%	3.75%	13.83%	310.30%
Monthly Fund Overpricing (FO)	40.86	40.86	5.00	0.01	37.74	44.02	93.98
Monthly Fund Underpricing (FU = 100-FO)	59.14	59.14	5.00	6.02	55.98	62.26	99.99
Active Fund Measure 1, AF1 [a]	0.38	0.37	0.11	0.00	0.30	0.45	0.99
Active Fund Measure 2, AF2 [b]	0.84	0.85	0.10	0.37	0.76	0.92	1.00
Active Fund Overpricing 1 (AFO1) [c]	0.29	0.26	1.62	−25.78	−0.50	1.08	19.91
Active Fund Overpricing 2 (AFO2) [d]	15.54	16.05	4.87	−7.69	12.10	19.32	46.99

[a] This measure of fund activeness is the **active weight** measure proposed by Doshi et al. (2015).

[b] This measure of fund activeness is the **active share** measure proposed by Cremers and Petajisto (2009).

[c] This measure of active fund overpricing is the weighted average of stock mispricing scores, where the weight applied to each stock held by the fund is the difference between the fund's weight in this stock and the weight that the stock would have been assigned had the manager market cap-weighted the equity portfolio.

[d] This measure of active fund overpricing is the weighted average of stock mispricing scores, where the weight applied to each stock held by the fund is the difference between the fund's weight in this stock and the stock's weight in the fund's benchmark portfolio, and is analogous to the measure proposed by Avramov et al. (2020).

Table 2. Characteristics of Subsets of Funds with Different Levels of Fund Underpricing

This table presents the average monthly characteristics for deciles of funds sorted in each month (t) within each investment style category by our measure of stock-picking skill, fund underpricing (FU). We present the average fund characteristics in each FU decile portfolio during month (t) to summarize the average fund characteristics across deciles of funds with a varying propensity to hold underpriced (or overpriced) stocks in the same month, t (see Avramov, Cheng, and Hameed, 2020, Table 2, and Lee et al., 2020, Table 7). The bottom row labeled ‘‘**H-L FU**’’ presents the difference in mean values for each variable between subsets of funds with high versus low fund underpricing (FU). The sample period extends from 1980 through 2024. 10%, 5% and 1% significance levels are denoted by *, **, and ***, respectively.

FU Portfolio	FU	Log(TNA)	Nstocks	RET	Exp_Ratio	Std_Ret	Fund_Flow	CR	CR_Buy	CR_Sell	CR_Buy − CR_Sell	(t-stat)
Low	**52.88**	**6.84**	**94**	**0.77%**	**0.99%**	**4.90%**	**−0.22%**	**4.25%**	**7.08%**	**7.72%**	**−0.64%**	**−4.13*****
2	55.30	7.00	124	0.87%	0.96%	4.70%	−0.09%	4.49%	7.19%	8.01%	−0.82%	−5.07***
3	56.53	7.12	131	0.89%	0.95%	4.63%	−0.01%	4.83%	7.72%	7.83%	−0.10%	−0.77
4	57.49	7.22	144	0.89%	0.94%	4.61%	0.00%	4.94%	7.73%	7.97%	−0.24%	−1.61
5	58.45	7.28	143	0.97%	0.94%	4.56%	0.03%	4.79%	7.43%	7.90%	−0.47%	−3.28***
6	59.21	7.16	154	0.98%	0.95%	4.47%	0.14%	4.66%	7.49%	7.58%	−0.09%	−0.64
7	60.23	7.10	151	0.97%	0.98%	4.43%	0.22%	4.56%	7.55%	7.49%	0.06%	0.38
8	61.34	7.05	130	1.00%	0.99%	4.40%	0.30%	4.76%	7.98%	7.98%	−0.01%	−0.04
9	62.96	6.85	120	1.03%	1.02%	4.39%	0.36%	4.75%	7.86%	8.14%	−0.29%	−1.65*
High	**66.26**	**6.71**	**105**	**1.07%**	**1.05%**	**4.35%**	**0.53%**	**4.47%**	**8.22%**	**7.92%**	**0.29%**	**1.45**
H−L FU	**13.38**	**−0.13**	**11**	**0.30%**	**0.06%**	**−0.54%**	**0.75%**	**0.22%**	**1.13%**	**0.20%**	**0.93%**	
t-stat	**190.38*****	**−4.28*****	**7.14*****	**3.62*****	**6.58*****	**−11.56*****	**7.62*****	**2.45****	**5.98*****	**1.03**	**3.92*****	

Table 3. Fund Underpricing, Total Fund Turnover, and Performance

This table provides monthly panel regression analysis that examines how fund performance in month t+1 is related to the fund's opportunity identification skill and trading intensity during month t, measured by fund underpricing (FU) and fund turnover (CR), respectively.

In Panel A, we first sort funds into terciles each month (t) within each investment style based on our measure FU. We then construct two indicator variables: one identifies funds that are more overpriced in the Lowest FU tercile (Low FU), and the other identifies funds that are more underpriced in the Highest FU tercile (High FU). In Panel A, column (1) includes both indicator variables without turnover. Columns (2) and (3) include each indicator variable separately, along with fund turnover (CR) and the corresponding interaction (Low FU×CR or High FU×CR). Column (4) includes both indicators, CR, and both interaction terms. The F-tests provided in columns (2) to (4) at the bottom of Panel A test the null hypotheses that the sum of the coefficients for CR and the interaction term between CR and either indicator variable (i.e., Low FU×CR or High FU×CR) is zero.

In Panel B, we provide a more parsimonious panel regression model that includes the continuous measure of fund underpricing (FU) itself, along with fund turnover (CR) and their interaction (FU×CR). Monthly performance for each fund (*f*) is measured by the Fama and French (2016) five-factor (FF5) alpha in month t+1 based on the fund's monthly gross return, expressed in percent. All panel regressions include style-by-month fixed effects, with standard errors clustered by fund. Numbers in parentheses are t-statistics. The 10%, 5% and 1% significance levels are denoted by *, **, and ***, respectively.

Panel A: Including Indicator Variables for Funds with High or Low Fund Underpricing

FF5 Alpha	(1)	(2)	(3)	(4)
Low FU	−0.008	0.014		0.017
	(−0.52)	(0.69)		(0.83)
High FU	0.029***		−0.003	0.005
	(3.69)		(−0.21)	(0.41)
CR		0.533***	0.127	0.333***
		(4.56)	(1.21)	(2.70)
Low FU×CR		**−0.625*** **		**−0.428** **
		(−3.27)		**(−2.12)**
High FU×CR			**0.603*** **	**0.399** **
			(3.28)	**(2.07)**
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Style x Time	Style x Time	Style x Time	Style x Time
Cluster	Fund	Fund	Fund	Fund
CR + Low FU×CR		−0.093		−0.095
F-test (p-value)		0.30 (0.583)		0.32 (0.571)
CR + High FU×CR			0.730***	0.731***
F-test (p-value)			17.66 (0.000)	17.75 (0.000)
Obs.	374,897	337,205	337,205	337,205
Adj. R^2	0.09	0.08	0.08	0.08

Table 3, continued

Panel B: Parsimonious Model: Including Continuous Measure of Fund Underpricing (FU)

FF5 Alpha	(1)	(2)	(3)
FU	0.005***	0.005**	0.002
	(2.60)	(2.47)	(0.76)
CR		0.340***	−3.739***
		(3.39)	(−2.72)
FU×CR			**0.068*** **
			(2.93)
Controls	Yes	Yes	Yes
Fixed Effects	Style x Time	Style x Time	Style x Time
Cluster	Fund	Fund	Fund
Obs.	374,897	337,205	337,205
Adj. R^2	0.09	0.08	0.08

Table 4. Fund Underpricing, Buy-Side versus Sell-Side Turnover, and Performance

This table provides monthly panel regression analysis that examines how fund performance in month t+1 is related to the fund's opportunity identification skill and trading intensity during month t, measured by fund underpricing (FU) and both buy and sell turnover (CR_Buy and CR_Sell), respectively. Here we repeat our estimation of the parsimonious model in Panel B of Table 3, but we separately include the components of total fund turnover (CR) comprised of purchases and sales, respectively. This analysis documents how the interaction between fund underpricing (FU) and buy-side or sell-side turnover (CR_Buy or CR_Sell) influences performance. Monthly fund performance is measured by the Fama and French (2016) five-factor (FF5) alpha in month t+1 based on the fund's monthly gross return, expressed in percent. All regressions include style-by-month fixed effects, with standard errors clustered by fund. Numbers in parentheses are t-statistics. The 10%, 5% and 1% significance levels are denoted by *, **, and ***, respectively.

FF5 Alpha	(1)	(2)	(3)
FU	0.002	0.004*	0.001
	(0.97)	(1.78)	(0.48)
CR_Buy	−1.985***		−1.987***
	(−2.88)		(−2.88)
FU×CR_Buy	**0.033*** **		**0.033*** **
	(2.89)		**(2.90)**
CR_Sell		−0.459	−0.488
		(−1.00)	(−1.07)
FU×CR_Sell		**0.009**	**0.009**
		(1.15)	**(1.22)**
Controls	Yes	Yes	Yes
Fixed Effects	Style x Time	Style x Time	Style x Time
Cluster	Fund	Fund	Fund
Obs.	337,205	337,205	337,205
Adj. R^2	0.08	0.08	0.08

Table 5. Alternative Fixed-Effect Structures in the Panel Regression Model

This table assesses the robustness of our baseline results from Tables 3 and 4 with respect to the choice of fixed-effect structures in our panel regression model. In particular, we provide results when we include both style and time fixed effects (not interacted), fund fixed effects only, and both fund and time fixed effects separately. For each structure of fixed effects, we provide the results for two regression models, one that includes total fund turnover (CR), and another that includes fund purchases and sales (CR_Buy and CR_Sell) separately. Monthly fund performance is measured by the Fama and French (2016) five-factor (FF5) alpha in month t+1 based on the fund's monthly gross return, expressed in percent. All regressions include standard errors clustered by fund. Numbers in parentheses are t-statistics. The 10%, 5% and 1% significance levels are denoted by *, **, and ***, respectively.

FF5 Alpha	(1) Model 1	(2) Model 2	(3) Model 1	(4) Model 2	(5) Model 1	(6) Model 2
FU	0.003	0.002	−0.002	−0.003	0.006***	0.006**
	(1.23)	(0.84)	(−0.31)	(−0.36)	(2.59)	(2.54)
CR	−4.253***		−6.692***		−5.064***	
	(−3.03)		(−3.88)		(−3.23)	
FU×CR	**0.077*** **		**0.120*** **		**0.090*** **	
	(3.25)		**(4.19)**		**(3.42)**	
CR_Buy		−2.068***		−2.871***		−2.101***
		(−2.95)		(−3.92)		(−2.92)
CR_Sell		−0.715		−1.334***		−0.653
		(−1.52)		(−2.74)		(−1.37)
FU×CR_Buy		**0.034*** **		**0.048*** **		**0.034*** **
		(2.94)		**(3.94)**		**(2.88)**
FU×CR_Sell		**0.013***		**0.024*** **		**0.012**
		(1.69)		**(2.87)**		**(1.53)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Style + Time	Style + Time	Fund	Fund	Fund + Time	Fund + Time
Cluster	Fund	Fund	Fund	Fund	Fund	Fund
Obs.	337,332	337,332	337,317	337,317	337,317	337,317
Adj. R^2	0.05	0.05	0.01	0.01	0.06	0.06

Table 6. Placebo Test: Fund Underpricing, Turnover, and Performance for Index Funds

This table provides our main monthly panel regression analysis applied to all *index funds*. In Panel A, the 'opportunity identification skills of index funds' are proxied by two indicator variables for subsets of overpriced or underpriced index funds (with Low or High FU) each month (t), while the 'trading intensity of index funds' is proxied by total fund turnover (CR). First, each month (t) we sort all index funds into terciles within each investment style based on FU. We then construct two indicator variables: one identifying 'unskilled, overpriced index funds' in the Lowest FU tercile, and another identifying 'skilled, underpriced index funds' in the Highest FU tercile. In Panel B, our regression model instead includes the continuous measure of fund underpricing (FU) for all index funds, along with index fund turnover (CR) and their interaction (FU×CR). Panel C includes both buy-side and sell-side turnover, as well as their interactions with FU. Index fund performance is measured by the Fama and French (2016) five-factor (FF5) alpha in month t+1 based on the fund's gross returns. All regressions include style-by-month fixed effects, with standard errors clustered by fund. Numbers in parentheses are t-statistics. The 10%, 5% and 1% significance levels are denoted by *, **, and ***, respectively.

Panel A: Indicator Variables for Index Funds with High or Low Levels of Fund Underpricing

FF5 Alpha	(1)	(2)	(3)	(4)
Low FU	−0.010	−0.015		−0.001
	(−0.88)	(−1.11)		(−0.08)
High FU	0.025		0.032	0.032
	(1.37)		(1.61)	(1.56)
CR		0.003	−0.132	−0.031
		(0.02)	(−0.79)	(−0.12)
Low FU×CR		**−0.191**		**−0.156**
		(−0.71)		**(−0.50)**
High FU×CR			**0.104**	**0.004**
			(0.29)	**(0.01)**
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Style x Time	Style x Time	Style x Time	Style x Time
Cluster	Fund	Fund	Fund	Fund
Obs.	58,614	54,878	54,878	54,878
Adj. R^2	0.14	0.14	0.14	0.14

Panel B: Continuous Measure of Fund Underpricing (FU) for Index Funds

FF5 Alpha	(1)	(2)	(3)
FU	0.013***	0.013***	0.015***
	(2.65)	(2.80)	(2.82)
CR		−0.040	2.269
		(−0.30)	(0.95)
FU×CR			**−0.039**
			(−0.99)
Controls	Yes	Yes	Yes
Fixed Effects	Style x Time	Style x Time	Style x Time
Cluster	Fund	Fund	Fund
Obs.	58,614	54,878	54,878
Adj. R^2	0.14	0.14	0.14

Table 6, continued

Panel C: Buy- and Sell-Side Turnover for Index Funds (CR_Buy and CR_Sell), Separately

FF5 Alpha	(1)	(2)	(3)
FU	0.008	0.013**	0.007
	(1.28)	(2.58)	(1.26)
CR_Buy	−2.749		−2.783
	(−0.81)		(−0.83)
FU×CR_Buy	**0.050**		**0.050**
	(0.87)		**(0.88)**
CR_Sell		0.083	−0.093
		(0.07)	(−0.09)
FU×CR_Sell		**−0.003**	**−0.000**
		(−0.16)	**(−0.00)**
Controls	Yes	Yes	Yes
Fixed Effects	Style x Time	Style x Time	Style x Time
Cluster	Fund	Fund	Fund
Obs.	54,878	54,878	54,878
Adj. R^2	0.14	0.14	0.14

Table 7. Fund Underpricing, Turnover, and Performance: The Impact of Fund Flows

This table provides monthly panel regression analysis that examines how fund performance in month t+1 is related to the fund's opportunity identification skill and trading intensity during month t, allowing the relations to differ during periods of large inflows or large outflows, through indicator variables and their interactions with FU, CR, and FU×CR. The dummy variable, Big Inflow, equals one for the subset of funds with positive fund flows that are above the median within the same month and investment style, and zero otherwise. The dummy variable, Big Outflow, equals one for the subset of funds with negative fund flows that are above the median within the same month and investment style, and zero otherwise. Monthly fund performance is measured by the Fama and French (2016) five-factor (FF5) alpha in month t+1 based on the fund's monthly gross return, expressed in percent. All regressions include style-by-month fixed effects, with standard errors clustered by fund. Numbers in parentheses are t-statistics. The 10%, 5% and 1% significance levels are denoted by *, **, and ***, respectively.

FF5 Alpha	(1)	(2)
FU	0.003 (0.88)	0.001 (0.43)
CR	**−3.793**** **(−2.07)**	**−3.733***** **(−2.78)**
FU×CR	**0.072**** **(2.33)**	**0.066***** **(2.86)**
Big Outflow	0.131 (0.80)	
Big Outflow × CR	0.205 (0.08)	
Big Outflow × FU	−0.002 (−0.88)	
Big Outflow × FU × CR	**−0.011** **(−0.26)**	
Big Inflow		−0.269 (−1.03)
Big Inflow × CR		0.431 (0.11)
Big Inflow × FU		0.004 (0.96)
Big Inflow × FU × CR		**0.009** **(0.12)**
Controls Fixed Effects Cluster	Yes Style x Time Fund	Yes Style x Time Fund
Obs. Adj. R^2	337,205 0.08	337,205 0.08

Table 8. Long-Run Predictability of Fund Underpricing and Turnover for Fund Performance

This table provides monthly panel regression analysis of how the fund's longer-term performance is associated with fund underpricing (FU) and fund turnover (CR). Future fund performance is measured by the fund's monthly Fama and French (2016) five-factor (FF5) alpha, in percent, over five different time frames. In the first column, we repeat the analysis from column (3) of Panel B in Table 3, analyzing future fund performance over month t+1. In the remaining columns, we analyze longer term future fund performance over months t+1 to t+3, t+4 to t+6, t+7 to t+9, and t+10 to t+12, respectively. All regressions include style-by-month fixed effects, with standard errors clustered by fund. Numbers in parentheses are t-statistics. The 10%, 5% and 1% significance levels are denoted by *, **, and ***, respectively.

FF5 Alpha	t+1	t+1:3	t+4:6	t+7:9	t+10:12
FU	0.002	0.002	0.002	−0.007	−0.004
	(0.76)	(0.30)	(0.44)	(−0.89)	(−0.65)
CR	−3.739***	−11.925***	−3.415	−7.569	−0.912
	(−2.72)	(−3.26)	(−0.84)	(−1.49)	(−0.20)
FU×CR	**0.068*** **	**0.210*** **	**0.073**	**0.139**	**0.028**
	(2.93)	**(3.39)**	**(1.09)**	**(1.61)**	**(0.36)**
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Style x Time	Style x Time	Style x Time	Style x Time	Style x Time
Cluster	Fund	Fund	Fund	Fund	Fund
Obs.	337,205	333,479	327,667	322,240	316,449
Adj. R^2	0.08	0.10	0.09	0.09	0.08

Table 9. Fund Underpricing, Turnover, and Performance during Periods of Market Stress

This table examines the robustness of our main results during periods of high market sentiment, volatility, or illiquidity. First, we construct three indicator variables (each labeled High) that equal one during months when each of these variables is above its sample median, and zero otherwise. Market sentiment is measured using the monthly investor sentiment index of Baker and Wurgler (2006). Market volatility is measured as the standard deviation of daily returns on the CRSP market portfolio during the month. Market-wide illiquidity is measured using the Pástor and Stambaugh (2003) illiquidity measure. For each measure of market stress identifying periods of high sentiment, volatility, or illiquidity, we add to our baseline regression model in Equation (3) the interactions of this indicator variable (High) with our main variables of interest (CR, FU, and FU×CR). Monthly fund performance is measured by the Fama and French (2016) five-factor (FF5) alpha in month t+1 based on the fund's monthly gross return, expressed in percent. All regressions include style-by-month fixed effects, with standard errors clustered by fund. Numbers in parentheses are t-statistics. The 10%, 5% and 1% significance levels are denoted by *, **, and ***, respectively.

FF5 Alpha	Sentiment		Volatility		Illiquidity	
	(1)	(2)	(3)	(4)	(5)	(6)
CR	0.183	0.115	0.013	−0.610	0.274***	−2.414
	(1.52)	(0.08)	(0.14)	(−0.45)	(2.71)	(−1.48)
CR×High	**0.355****	**−9.851*****	**0.708*****	**−6.798****	**0.081**	**−2.508**
	(2.00)	**(−3.21)**	**(4.53)**	**(−2.45)**	**(0.58)**	**(−1.08)**
FU		0.004**		−0.005**		−0.002
		(2.12)		(−2.53)		(−0.67)
FU×High		−0.006		0.016***		0.008**
		(−1.28)		(3.74)		(2.38)
FU×CR		**0.002**		**0.010**		**0.046***
		(0.10)		**(0.45)**		**(1.69)**
FU×CR×High		**0.171*****		**0.130*****		**0.043**
		(3.31)		**(2.75)**		**(1.11)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Style x Time	Style x Time	Style x Time	Style x Time	Style x Time	Style x Time
Cluster	Fund	Fund	Fund	Fund	Fund	Fund
Obs.	365,406	337,205	365,406	337,205	365,406	337,205
Adj. R^2	0.09	0.08	0.09	0.08	0.09	0.08

Table 10. Alternative Measures of Fund Skill

This table analyzes how fund performance depends on several alternative measures of fund skill, portfolio liquidity, fund activeness and/or mispricing by themselves, as well as interacted with turnover (CR). In Panel A, we ***replace*** our measure of fund underpricing and its interaction with CR (FU and FU×CR) in Equation (3) with each alternative measure, including the fund expense ratio (Exp_Ratio), the average FF5 over the last 12 months (Past_FF5), the portfolio liquidity measure of Pástor, Stambaugh, and Taylor (2020, L), the 'active weight' measure from Doshi et al. (2015, AF1), the 'active share' measure of Cremers and Petajisto (2009, AF2), another measure of active fund overpricing that combines the 'active weights' from Doshi et al. (2015) with the stock mispricing measure (MISP) from Stambaugh, Yu, and Yuan (2015, AFO1), and the active fund overpricing measure of Avramov et al. (2020, AFO2) that combines 'active share' of Cremers and Petajisto (2009) with MISP. In Panel B, we ***append*** Equation (3) to include FU, FU×CR, and each alternative measure plus its interaction with CR. Monthly performance is the Fama and French (2016) five-factor (FF5) alpha in month t+1. We include style-by-month fixed effects, and cluster standard errors by fund. Numbers in parentheses are t-statistics. The 10%, 5% and 1% significance levels are denoted by *, **, and ***, respectively.

Panel A: Alternative Fund Characteristics Related to Skill, Liquidity, Activeness, and Mispricing (Exp_Ratio, L, AF1, AF2, AFO1, and AFO2)

VARIABLES	(1) FF5	(2) FF5	(3) FF5	(4) FF5	(5) FF5	(6) FF5	(7) FF5	(8) FF5	(9) FF5	(10) FF5	(11) FF5	(12) FF5	(13) FF5	(14) FF5	(15) FF5
Exp_Ratio	3.797***							1.727							-0.595
	(3.04)							(1.02)							(-0.34)
CR								-0.141	0.301***	0.381***	-0.307	-0.527	0.345***	0.226**	-0.064
								(-0.56)	(3.32)	(2.65)	(-0.85)	(-0.70)	(3.30)	(2.10)	(-0.06)
Exp_Ratio_x_CR								**39.004**							**30.241**
								(1.59)							**(1.27)**
Past_FF5		0.101***							0.099***						0.068**
		(12.57)							(3.69)						(2.32)
Past_FF5_x_CR									**0.101**						**0.202**
									(0.20)						**(0.87)**
L			0.021							0.100					0.029
			(0.25)							(1.36)					(0.30)
L_x_CR										**-1.670**					**-0.368**
										(-1.22)					**(-0.23)**
AF1				0.122**							0.002				0.013
				(2.52)							(0.02)				(0.18)
AF1_x_CR											**1.482**				**1.441**
											(1.53)				**(1.63)**
AF2					-0.082							-0.117**			-0.207**
					(-1.44)							(-2.00)			(-2.48)
AF2_x_CR												**0.979**			**-0.699**
												(1.04)			**(-0.56)**
AFO1						-0.005							0.002		-0.002
						(-1.36)							(0.35)		(-0.30)
AFO1_x_CR													**-0.170****		**-0.106**
													(-2.41)		**(-1.44)**
AFO2							-0.002							0.003	0.003
							(-0.61)							(0.79)	(0.95)
AFO2_x_CR														**-0.090****	**-0.047**
														(-2.03)	**(-0.94)**
Observations	405,532	436,822	405,713	405,713	394,171	405,113	405,113	365,406	394,077	365,499	365,499	394,097	364,954	364,954	358,866
Adjusted R^2	0.09	0.09	0.09	0.09	0.08	0.09	0.09	0.09	0.09	0.08	0.08	0.08	0.08	0.08	0.09
controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fixed Effects	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time
Cluster	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund

Table 10, continued

Panel B: Alternative Fund Characteristics Related to Skill, Liquidity, Activeness, and Mispricing, Controlling for Our Proposed Measure of Fund Underpricing (FU and FU×CR)

VARIABLES	(1) FF5	(2) FF5	(3) FF5	(4) FF5	(5) FF5	(6) FF5	(7) FF5	(8) FF5
CR	-4.361***	-3.495***	-3.838***	-4.149***	-5.306***	-2.884**	-3.307**	-4.252**
	(-2.89)	(-2.66)	(-2.84)	(-2.90)	(-2.95)	(-1.99)	(-2.09)	(-1.97)
FU	0.002	0.001	0.002	0.002	0.002	0.003	0.008***	0.007***
	(0.71)	(0.37)	(0.90)	(1.00)	(0.79)	(1.23)	(3.33)	(2.88)
FU_x_CR	**0.070*** **	**0.064*** **	**0.071*** **	**0.065*** **	**0.073*** **	**0.054** **	**0.060** **	**0.059** **
	(2.96)	**(2.85)**	**(3.05)**	**(2.86)**	**(3.11)**	**(2.20)**	**(2.20)**	**(2.17)**
Exp_Ratio	1.280							2.150
	(0.65)							(1.17)
Exp_Ratio_x_CR	**45.550**							**29.490**
	(1.62)							**(1.12)**
Past_FF5		0.111***						0.096***
		(3.79)						(6.43)
Past_FF5_x_CR		**-0.001**						**0.095**
		(-0.00)						**(0.24)**
L			0.097					-0.081
			(1.35)					(-0.71)
L_x_CR			**-2.403***					**-0.504**
			(-1.65)					**(-0.31)**
AF1				-0.015				-0.043
				(-0.21)				(-0.51)
AF1_x_CR				**1.402**				**1.072**
				(1.35)				**(1.07)**
AF2					-0.133**			-0.061
					(-2.10)			(-0.72)
AF2_x_CR					**1.541**			**0.425**
					(1.49)			**(0.31)**
AFO1						0.004		0.003
						(0.81)		(0.46)
AFO1_x_CR						**-0.114**		**-0.125**
						(-1.43)		**(-1.58)**
AFO2							0.015***	0.015***
							(3.61)	(3.71)
AFO2_x_CR							**-0.020**	**0.025**
							(-0.38)	**(0.47)**
Observations	337,205	364,934	364,954	364,954	364,954	364,954	364,954	337,205
Adjusted R^2	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.09
controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed Effects	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time	Style*Time
Cluster	Fund	Fund	Fund	Fund	Fund	Fund	Fund	Fund

Internet Appendix
The Ability of Mutual Fund Managers to Identify Underpriced Securities and the Relation between Fund Turnover and Performance

Table IA.1 Detailed Variable Definitions

TNA = Fund Total Net Assets	Fund total net assets (TNA) is obtained from CRSP Mutual Fund Database (MFDB). CRSP measures TNA as total assets minus total liabilities at month-end. Reported in millions of dollars.
Family_Size = Fund Family Size	Total TNA of all funds within the fund's family at month-end. Reported in millions of dollars.
RET_t = Fund Net Return in Month *t*	Monthly net return for each mutual fund share class is obtained from CRSP Mutual Fund Database (MFDB). CRSP measures. CRSP calculates monthly net return as the percentage change in net asset value, inclusive of dividend and capital gains distributions, and net of total expenses, following the definition in the CRSP Survivor-Bias-Free US Mutual Fund Database (MFDB) Guide (2023, p. 9). For funds with multiple share classes, we compute fund-level net returns by the TNA-weighted average across all share classes. The weights are based on the previous month's total net assets of each share class in the same fund.
$RRET_t$ = Fund Gross Return in Month *t*	Monthly fund-level gross return for each mutual fund share class is calculated as the sum of fund-level monthly net returns and 1/12 of the annual expense ratio.
$HRET_t$ = Fund Holdings Return in Month *t*	Monthly holdings return for each mutual fund *f* in month *t* is defined as the total return of a hypothetical buy-and-hold portfolio formed from the stock positions reported at the most recent disclosure date at time $t-\tau$ (Kacperczyk, Sialm, and Zheng, 2008): $HRET_{f,t} = \sum_{i=1}^{n} {w_{i,t-1}}^{f} \times R_{i,t}$, where ${w_{i,t-1}}^{f} = \frac{Prc_{i,t-1} \times Shares\ held_{i,f,t-\tau}}{\sum_{i=1}^{N_f} Prc_{i,t-1} \times Shares\ held_{i,f,t-\tau}}$, $R_{i,t}$ is the return of stock i in month *t*. The weight, ${w_{i,t-1}}^{f}$, is the value of stock *i* owned by fund *f* as a percentage of the total value of all stocks held by fund *f* prior to month *t*. $Prc_{i,t-1}$ is the price of stock *i* at the end of the previous month. $Shares\ held_{i,f,t-\tau}$ reflects the number of shares of stock *i* held by fund *f* on the most recent quarterly disclosure date at time $t-\tau$. N_f denotes the number of stocks in the portfolio of fund *f* in each quarter.
CAPM = CAPM Alpha	For each fund, we estimate monthly alpha from the CAPM model, to measure the fund's market-adjusted abnormal return. First, in each month *t*, we estimate a rolling regression of fund excess return on the market excess return using the previous 36 months. The regression coefficient ($\hat{b}_{f,t-1}$) captures the fund's exposure to the market factor over the previous 36 months. Second, our estimate of the fund's monthly alpha in month *t* is the realized return not explained by lagged factor exposures: $\hat{\alpha}_{f,t}^{CAPM} = R_{f,t} - RF_t - \left[\hat{b}_{f,t-1}(\mathrm{MKT}_t - RF_t)\right]$ (see Ben-David et al., 2022; Irvine, Kim, and Ren, 2024).

FF4 = FF4 Alpha	For each fund, we estimate monthly alpha from the Carhart (1997) four-factor model. Our estimate of the fund's monthly alpha is the realized return not explained by the lagged factor exposures: $\hat{\alpha}_{f,t}^{\mathrm{FF4}} = R_{f,t} - RF_t - \left[\hat{b}_{f,t-1}(\mathrm{MKT}_t - RF_t) + \hat{s}_{f,t-1}\mathrm{SMB}_t + \hat{h}_{f,t-1}\mathrm{HML}_t + \hat{u}_{f,t-1}\mathrm{UMD}_t\right]$, where $\hat{b}_{f,t-1}, \hat{s}_{f,t-1}, \hat{h}_{f,t-1}$, and $\hat{u}_{f,t-1}$ are the estimated regression coefficients based on a rolling regression estimated over the previous 36 months.
FF5 = FF5 Alpha	For each fund, we estimate monthly alpha from the Fama French five-factor model. Our estimate of the fund's monthly alpha is the realized return not explained by the lagged factor exposures: $\hat{\alpha}_{f,t}^{\mathrm{FF5}} = R_{f,t} - RF_t - \left[\hat{b}_{f,t-1}(\mathrm{MKT}_t - RF_t) + \hat{s}_{f,t-1}\mathrm{SMB}_t + \hat{h}_{f,t-1}\mathrm{HML}_t + \hat{r}_{f,t-1}\mathrm{RMW}_t + \hat{c}_{f,t-1}\mathrm{CMA}_t\right]$, where $\hat{b}_{f,t-1}, \hat{s}_{f,t-1}, \hat{h}_{f,t-1}, \hat{r}_{f,t-1}$, and $\hat{c}_{f,t-1}$ are the estimated regression coefficients.
FFL = FFL Alpha	For each fund, we estimate monthly alpha from the five-factor model that includes the Carhart four factors plus a liquidity factor (LIQ_t). Our estimate of the fund's monthly alpha is the realized return not explained by the lagged factor exposures: $\hat{\alpha}_{f,t}^{\mathrm{FFL}} = R_{f,t} - RF_t - \left[\hat{b}_{f,t-1}(\mathrm{MKT}_t - RF_t) + \hat{s}_{f,t-1}\mathrm{SMB}_t + \hat{h}_{f,t-1}\mathrm{HML}_t + \hat{u}_{f,t-1}\mathrm{UMD}_t + \hat{l}_{f,t-1}\mathrm{LIQ}_t\right]$, where $\hat{b}_{f,t-1}, \hat{s}_{f,t-1}, \hat{h}_{f,t-1}, \hat{u}_{f,t-1}$, and $\hat{l}_{f,t-1}$ are the estimated regression coefficients.
FFM = FFM Alpha	For each fund, we estimate monthly alpha from the five-factor model that includes the Carhart four factors plus a mispricing factor (MISP_t). Our estimate of the fund's monthly alpha is the realized return not explained by the lagged factor exposures: $\hat{\alpha}_{f,t}^{\mathrm{FFL}} = R_{f,t} - RF_t - \left[\hat{b}_{f,t-1}(\mathrm{MKT}_t - RF_t) + \hat{s}_{f,t-1}\mathrm{SMB}_t + \hat{h}_{f,t-1}\mathrm{HML}_t + \hat{u}_{f,t-1}\mathrm{UMD}_t + \hat{m}_{f,t-1}\mathrm{MISP}_t\right]$, where $\hat{b}_{f,t-1}, \hat{s}_{f,t-1}, \hat{h}_{f,t-1}, \hat{u}_{f,t-1}$, and $\hat{m}_{f,t-1}$ are the estimated regression coefficients.
Past_FF5 = Past FF5 Alpha	We compute Past_FF5 Alpha as the average FF5 over the last 12 months.
Flow_Mon = Monthly Fund Flow	The fund flow of fund *f* during month *t* is calculated by taking the difference between the current month's TNA and the previous month's TNA, adjusted for the return aggregated across all share classes (weighted by TNA of each share class) in month *t*. This total is then normalized (scaled) by the fund's TNA at the end of month *t-1* to measure the fund flow for month *t*. Thus the fund flow of fund *f* in month t is given by $\frac{(\mathrm{TNA})_{f,t} - (\mathrm{TNA})_{f,t-1} * (1+R_{f,t})}{(\mathrm{TNA})_{f,t-1}}$, where $R_{f,t}$ is the return aggregated across all share classes (weighted by TNA of each share class) of fund *f* in month t, and $(\mathrm{TNA})_{f,t}$ represents the total net asset for fund *f* in month *t.*
Exp_Ratio = Expense Ratio	The Expense Ratio for fund *f* in month *t* is the fund's expense ratio over the most recent fiscal year prior to month *t.* This expense ratio is the percentage of the fund's total investment that shareholders pay for the fund's operating expenses.
Std_Ret = Return Volatility	Standard deviation of monthly fund returns over the previous 24 months (*t-24* through *t-1*).

FO = Monthly Fund Overpricing	The fund overpricing (FO) measure for fund *f* in month *t* is the weighted average of the firm-specific mispricing scores (MISP of Stambaugh, Yu, and Yuan, 2015) across all stocks (*i*) held by the fund[29]: $FO_{f,t} = \sum_{i=1}^{N_f} {w_{i,t}}^{f} \times MISP_{i,t}$, where ${w_{i,t}}^{f} = \frac{Prc_{i,t} \times Shares\ held_{i,f,t-\tau}}{\sum_{i=1}^{N_f} Prc_{i,t} \times Shares\ held_{i,f,t-\tau}}$, The weight, ${w_{i,t}}^{f}$, is the value of stock *i* owned by fund *f* as a percentage of the total value of all stocks held by fund *f* at the end of month *t*. $Prc_{i,t}$ is the price of stock *i* at the end of month *t*. $Shares\ held_{i,f,t-\tau}$ reflects the number of shares of stock *i* held by fund manager *f* on the most recent quarterly disclosure at time $t-\tau$. N_f denotes the number of stocks in the portfolio of fund *f* in each quarter. Stock-level mispricing data (MISP) are obtained from Stambaugh, Yu, and Yuan (2015) and Han et al. (2022), and are available from 1963 to 2019.[30] We extend the mispricing data to 2024.
FU = Monthly Fund Underpricing	The fund underpricing (FU) measure for fund *f* in month *t* is computed as 100 minus the monthly fund overpricing measure.
AF1 = Fund Activeness Measure by Doshi et al. (2015)	We use the "Active Weight" measure in Doshi et al. (2015) as fund activeness (AF1) measure for fund *f* in month *t*. According to Doshi et al. (2015), AF1 reflects one half of the absolute difference between fund's weight applied to each stock and the value weight (i.e., the weight that the stock would have been assigned had the manager market cap-weighted the equity portfolio): $AF1_{f,t} = \frac{1}{2} \sum_{i=1}^{N_f} \left| {w_{i,t}}^{f} - {w_{i,t}}^{fm} \right|$, where ${w_{i,t}}^{f} = \frac{Prc_{i,t} \times Shares\ held_{i,f,t-\tau}}{\sum_{i=1}^{N_f} Prc_{i,t} \times Shares\ held_{i,f,t-\tau}}$, ${w_{i,t}}^{fm} = \frac{Prc_{i,t} \times Shrout_{i,t}}{\sum_{i=1}^{N_f} Prc_{i,t} \times Shrout_{i,t}}$ The weight, ${w_{i,t}}^{f}$, is the weight of stock *i* in fund *f*'s equity portfolio in month *t*. The weight, ${w_{i,t}}^{fm}$ is the weight of stock *i* in the market cap-weighted equity portfolio in the same month *t*, which shows the weight that the stock would have been assigned had the manager market cap-weighted the equity portfolio. N_f denotes the number of stocks in the portfolio of fund *f* in the current quarter.
AF2 = Fund Activeness Measure by Cremers and Petajisto (2009)	We use an "Active Share" measure similar to Cremers and Petajisto (2009) as our second fund activeness measure. For fund *f* in month *t*, AF2 is the Active Share over the most recent quarter prior to month *t* (i.e., quarter *t-1*). According to Cremers and Petajisto (2009), this measure is one half of the sum of absolute differences between the fund's portfolio weight in each stock and the corresponding benchmark weight, as follows: $AF2_{f,T} = \frac{1}{2} \sum_{i=1}^{N} \left| {w_{i,T}}^{f} - {w_{i,T}}^{fb} \right|$,

[29] Since quarterly fund holdings data are available from 1980 onward, the overlap in data availability defines our sample period of 1980–2024 for analyzing the behavior of fund mispricing and turnover. Note that FO varies across quarters due to quarterly changes in fund holdings, but also across months due to monthly changes in mispricing scores (MISP) for the individual stockholdings of the fund.

[30] We thank Robert F. Stambaugh for providing stock-level mispricing data (MISP) from 1963 to 2016 (https://finance.wharton.upenn.edu/~stambaug/), and Guofu Zhou for extending these data through 2019 (https://apps.olin.wustl.edu/faculty/zhou/zpublications.html).

	where $w_{i,T}{}^{f} = \frac{Prc_{i,T} \times Shares\ held_{i,f,T}}{\sum_{i=1}^{N_f} Prc_{i,T} \times Shares\ held_{i,f,\mathrm{T}}}, w_{i,T}{}^{fb} = \frac{Prc_{i,T} \times Shares\ held_{i,fb,T}}{\sum_{i=1}^{N_{fb}} Prc_{i,T} \times Shares\ held_{i,fb,\mathrm{T}}},$ The weight, $w_{i,T}{}^{f}$, is the weight of stock *i* in fund *f*'s equity portfolio at the end of quarter *T*. The weight, $w_{i,T}{}^{fb}$ is the weight of stock *i* in the fund's benchmark portfolio in the same quarter *T*. We generate nine potential benchmark portfolios to match with each fund by double-sorting all CRSP common stocks on firm size and industry-adjusted book-to-market, following Daniel, Grinblatt, Titman, and Wermers (1997). For each fund in each quarter, we compute Active Share relative to each of the nine candidate benchmark portfolios. We select the portfolio that provides the lowest Active Share as the fund's benchmark and hold this choice fixed for the following three months. AF2 measures fund managerial activeness by one half of the sum of absolute deviations, $(w_{i,T}{}^{f} - w_{i,T}{}^{fb})$, which capture the differences between the actual weights on each stock held by a fund and that stock's weight in this fund's benchmark portfolio. $Shares\ held_{i,f,\mathrm{T}}$ reflects the number of shares of stock *i* held by fund manager *f* in quarter *T*. N_f denotes the number of stocks in the portfolio of fund *f* in the current quarter. $Shares\ held_{i,fb,\mathrm{T}}$ reflects the number of shares of stock *i* in the fund's benchmark portfolio *fb* in quarter *T*. N_{fb} denotes the number of stocks in the fund benchmark portfolio in the current quarter. N denotes the number of stocks either in the portfolio of fund *f* or in the fund benchmark portfolio in the current quarter.
AFO1 = Monthly Fund Overpricing to Market Portfolio	The fund active overpricing (AFO1) measure for fund *f* in month *t* is the weighted average of the firm-specific mispricing scores (MISP) for stocks held by the fund, where the weights reflect the difference between the fund's weight applied to each stock and the value weight (i.e., the weight that the stock would have been assigned had the manager market cap-weighted the equity portfolio), as follows: $$AFO1_{f,t} = \frac{1}{2} \sum_{i=1}^{N_f} (w_{i,t}{}^{f} - w_{i,t}{}^{fm}) \times MISP_{i,t},$$ where $w_{i,t}{}^{f} = \frac{Prc_{i,t} \times Shares\ held_{i,f,t-\tau}}{\sum_{i=1}^{N_f} Prc_{i,t} \times Shares\ held_{i,f,t-\tau}}, w_{i,t}{}^{fm} = \frac{Prc_{i,t} \times Shrout_{i,t}}{\sum_{i=1}^{N_f} Prc_{i,t} \times Shrout_{i,t}}$ The weight, $w_{i,t}{}^{f}$, is the weight of stock *i* in fund *f*'s equity portfolio in month *t*. The weight, $w_{i,t}{}^{fm}$ is the weight of stock *i* in the market cap-weighted equity portfolio (Doshi et al., 2015) in the same month *t*. The active fund overpricing measure (AFO1) is constructed in a manner similar to Avramov et al. (2020). However, rather than using each fund's individual benchmark weight for a given stock, we construct the benchmark weight as in AF1 (Doshi et al., 2015), using all stocks held by the funds and weighting them by market capitalization.
AFO2 = Monthly Fund Overpricing to Fund Benchmark Portfolio	The fund active overpricing (AFO2) measure for fund *f* in month *t* is the weighted average of the firm-specific mispricing scores (MISP) for stocks held by the fund, where the weights reflect the difference between the fund's weight applied to each stock and that stock's weight in the fund benchmark index (Avramov et al., 2020): $$AFO2_{f,t} = \frac{1}{2} \sum_{i=1}^{N} (w_{i,t}{}^{f} - w_{i,t}{}^{fb}) \times MISP_{i,t},$$

	where $w_{i,t}{}^{f} = \frac{Prc_{i,t} \times Shares\ held_{i,f,t-\tau}}{\sum_{i=1}^{N_f} Prc_{i,t} \times Shares\ held_{i,f,t-\tau}}$, $w_{i,t}{}^{fb} = \frac{Prc_{i,t} \times Shares\ held_{i,fb,t-\tau}}{\sum_{i=1}^{N_{fb}} Prc_{i,t} \times Shares\ held_{i,fb,t-\tau}}$, The weight, $w_{i,t}{}^{f}$, is the weight of stock *i* in fund *f*'s equity portfolio in month *t*. The weight, $w_{i,t}{}^{fb}$ is the weight of stock *i* in the fund benchmark portfolio in the same month *t*. Similar to AF2 described above, we generate nine potential benchmark portfolios by double-sorting all CRSP common stocks on firm size and industry-adjusted book-to-market. For each fund in each quarter, we compute Active Share relative to each of the nine candidate benchmark portfolios. We select the portfolio that provides the lowest Active Share as the fund's benchmark and hold this choice fixed for the following three months. AFO2 captures activeness of fund investment in mispriced stocks, and measures fund managerial activeness by summing over the deviations between each stock's actual weight in the fund portfolio and that stock's weight in this benchmark portfolio, $(w_{i,t}{}^{f} - w_{i,t}{}^{fb})$. $Shares\ held_{i,f,t-\tau}$ reflects the number of shares of stock *i* held by fund manager *f* on the most recent quarterly disclosure at time $t-\tau$. N_f denotes the number of stocks in the portfolio of fund *f* in the current quarter. $Shares\ held_{i,fb,t-\tau}$ reflects the number of shares of stock *i* in the fund's benchmark portfolio *fb* at time $t-\tau$. N_{fb} denotes the number of stocks in the fund benchmark portfolio in the current quarter. N denotes the number of stocks either in the portfolio of fund *f* or in the fund benchmark portfolio in the current quarter. This definition of AFO2 is similar in spirit to Cremers and Petajisto (2009), but we use nine benchmarks based on size and industry-adjusted book-to-market while they use fund-specific benchmark index as fund reference portfolio.
CR = Churn Rate (Portfolio Turnover)	Fund portfolio turnover for fund *f* in month *t* is the churn rate over the most recent quarter prior to month *t* (i.e., quarter *T-1*), defined as the minimum of the fund's total purchases or sales made during the past quarter (from quarter *T-2* to *T-1*), scaled by the fund's average total quarterly holdings over the quarter *T-2* and quarter *T-1*, following Yan and Zhang (2009). Specifically, each quarter, we first calculate the aggregate purchases (or sales) for each institution, as the aggregate increase (or decrease) in the fund's holdings across all stocks purchased (or sold) in its portfolio, as follows: $Assets_buy_{f,T-1} = \sum_{i=1}^{N_f} \left| S_{f,i,T-1} P_{i,T-1} - S_{f,i,T-2} P_{i,T-2} - S_{f,i,T-2} \Delta P_{i,T-1} \right|$ $S_{f,i,T-1} > S_{f,i,T-2}$ $Assets_sell_{f,T-1} = \sum_{i=1}^{N_f} \left| S_{f,i,T-1} P_{i,T-1} - S_{f,i,T-2} P_{i,T-2} - S_{f,i,T-2} \Delta P_{i,T-1} \right|$ $S_{f,i,T-1} \leqslant S_{f,i,T-2}$ where $P_{i,T-2}$ and $P_{i,T-1}$ are the share prices for stock i at the end of quarters $T-2$ and $T-1$, respectively, and $S_{f,i,T-2}$ and $S_{f,i,T-1}$ are the number of shares of stock i held by institution f at the end of quarters $T-2$ and $T-1$, respectively. Thus, $Assets_buy_{f,T-1}$ and $Assets_sell_{f,T-1}$ represent institution f 's aggregate purchases and sales for quarter $T-1$, respectively. Then, institution f 's portfolio turnover (proxied by the churn rate) for quarter $T-1$ is defined as:

	$$CR_{f,\mathrm{T}-1} \equiv \frac{\min\left(Assets_buy_{f,\mathrm{T}-1},\ Assets_sell_{\ f,\mathrm{T}-1}\right)}{\sum_{i=1}^{N_f} \frac{S_{f,i,\mathrm{T}-1}P_{i,\mathrm{T}-1} + S_{f,i,\mathrm{T}-2}P_{i,\mathrm{T}-2}}{2}}$$
CR_Buy = Buy Portfolio Turnover	Similar to portfolio turnover, institution f 's buy portfolio turnover for quarter $T-1$ is defined as: $$CR_buy_{f,\mathrm{T}-1} \equiv \frac{Assets_buy_{f,\mathrm{T}-1}}{\sum_{i=1}^{N_f} \frac{S_{f,i,\mathrm{T}-1}P_{i,\mathrm{T}-1} + S_{f,i,\mathrm{T}-2}P_{i,\mathrm{T}-2}}{2}}$$
CR_Sell = Sell Portfolio Turnover	Similar to portfolio turnover, institution f 's sell portfolio turnover for quarter $T-1$ is defined as: $$CR_sell_{f,\mathrm{T}-1} \equiv \frac{Assets_sell_{\ f,\mathrm{T}-1}}{\sum_{i=1}^{N_f} \frac{S_{f,i,\mathrm{T}-1}P_{i,\mathrm{T}-1} + S_{f,i,\mathrm{T}-2}P_{i,\mathrm{T}-2}}{2}}$$
High_FU	In each month *t*, all funds within each style category are sorted into terciles by FU. High_FU = 1 if the FU for fund *f* in month *t* belongs to the highest FU tercile across all funds of the same style in month *t*; otherwise, High_FU = 0.
Low_FU	Similar to High_FU, Low_FU = 1 if the FU for fund *f* in month *t* belongs to the lowest FU tercile across all funds of the same style in month *t.*
ILLIQ = Amihud illiquidity	Amihud (2002) illiquidity measure (ILLIQ) for fund *f* in month *t* is the weighted-average of Amihud illiquidity across all stocks (*i*) held by the fund. Amihud illiquidity of stock *i* in month *t* (ami_126d) is obtained from WRDS - Contributed Data Forms - Global Stock Returns and Characteristics.
Funding_Cond = Funding Conditions	The funding environment in month *t* is deemed to be expansive (restrictive) when the most recent change in both the federal funds rate and the federal discount rate is a decline (increase). The funding environment is labeled as indeterminate for all other months when the most recent changes in the federal funds rate and the federal discount rate are in different directions.
L = Portfolio liquidity	We construct portfolio liquidity following Pástor, Stambaugh, and Taylor (2020). Portfolio liquidity of fund *f* in month *t* is defined as: $$L_{f,t} = \left(\sum_{i=1}^{N_f} \frac{(w_{i,t}{}^{f})^2}{m_{i,t}} \right)^{-1},$$ where N_f is the number of stocks in the fund *f*'s portfolio in the current quarter, $w_{i,t}{}^{f}$ is the fund *f*'s weight on stock *i* in month *t* and $m_{i,t}$ denotes the weight on stock *i* in month *t* in a market-cap-weighted benchmark portfolio of all CRSP stocks in the market.

Table IA.2. The Relation between Fund Underpricing and Two Measures of Managerial Timing and Stock-Picking Skills

This table provides monthly panel regression analysis that examines how two measures of fund managerial timing and stock-picking abilities (labeled 'Timing' and 'Picking,' from Kacperczyk, van Nieuwerburgh, and Veldkamp, 2014) during month (t+1) are related to our proposed measures of a fund's stock-picking (FU) during month (t). All regressions include style-by-month fixed effects, with standard errors clustered by fund. Numbers in parentheses are t-statistics. The 10%, 5% and 1% significance levels are denoted by *, **, and ***, respectively.

Dependent Variable:	Timing	Picking
	(1)	(4)
FU	−0.007***	0.015***
	(−7.00)	(10.44)
Controls	Yes	Yes
Fixed Effects	Style x Time	Style x Time
Cluster	Fund	Fund
Obs.	354,615	354,615
Adj. R^2	0.94	0.35

Table IA.3. The Persistence of Stock-Picking Skill (Fund Underpricing) for Mutual Funds

Panels A to C of this table present transition matrices that document the percentage of mutual funds in the top, middle, or bottom deciles (i.e., D10, D5, and D1), respectively, sorted by fund underpricing (FU) in month (t) that continue to remain in the same decile (i.e., D10, D5, or D1) during each of the subsequent 12 months (t+1 to t+12) in **bold**, as well as the percentage of funds that move to each of the other FU deciles. For every month (t), we first rank all mutual funds into deciles by our measure of fund underpricing (FU). D1 refers to the lowest FU decile, D5 to the middle FU decile, and D10 to the highest FU decile. We then present the percentage of funds in each of these three FU deciles (i.e., D10, D5, or D1) that remain in the same FU decile in **bold**, as well as the percentages of funds that move to all of the other FU deciles, during each of the following 12 months. In each panel, columns D1–D10 denote destination deciles, and rows 1–12 denote horizons t+1 through t+12.

Panel A: Subset of Funds with High Stock-Picking Skill in Month *t*, Proxied by High Levels of Fund Underpricing in FU Decile 10

Fund	Horizon (t+i)	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
D10 funds	1	0.93%	1.53%	1.45%	1.44%	1.96%	2.02%	2.31%	3.74%	12.51%	**80.10%**
in Month (t)	2	1.00%	1.36%	1.69%	1.75%	2.14%	2.22%	2.81%	4.83%	16.28%	**70.88%**
	3	1.07%	1.44%	1.84%	1.99%	2.16%	2.49%	3.50%	6.03%	18.07%	**66.39%**
	4	1.37%	1.62%	2.13%	2.29%	2.43%	2.93%	4.19%	7.00%	18.29%	**60.72%**
	5	1.67%	1.91%	2.39%	2.63%	2.67%	3.30%	4.70%	8.00%	18.93%	**57.46%**
	6	1.91%	2.12%	2.54%	2.76%	2.97%	3.76%	5.18%	8.71%	19.68%	**55.90%**
	7	2.14%	2.52%	2.77%	2.87%	3.38%	3.94%	5.69%	9.07%	19.08%	**51.50%**
	8	2.27%	2.68%	3.01%	3.01%	3.61%	4.19%	6.07%	9.36%	18.81%	**48.69%**
	9	2.44%	2.90%	3.04%	3.29%	3.77%	4.49%	6.44%	10.11%	18.71%	**47.35%**
	10	2.60%	3.08%	3.13%	3.60%	3.81%	4.74%	6.87%	10.26%	18.15%	**44.49%**
	11	2.80%	3.24%	3.25%	3.89%	3.97%	5.13%	7.15%	10.66%	17.88%	**43.20%**
	12	2.96%	3.21%	3.45%	3.94%	4.19%	5.44%	7.62%	11.00%	18.26%	**42.53%**

Panel B: Subset of Funds with Medium Stock-Picking Skill in Month *t*, Proxied by Medium Levels of Fund Underpricing in FU Decile 5

Fund	Horizon (t+i)	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
D5 funds	1	1.75%	3.04%	5.51%	18.46%	**48.26%**	17.34%	6.00%	3.39%	2.67%	2.29%
in Month (t)	2	2.14%	3.79%	7.49%	19.97%	**34.60%**	18.49%	7.62%	4.41%	3.00%	2.03%
	3	2.59%	4.58%	8.76%	19.64%	**28.76%**	18.54%	9.00%	5.06%	3.20%	2.14%
	4	3.03%	5.41%	9.79%	18.11%	**24.94%**	17.75%	9.60%	5.68%	3.80%	2.40%
	5	3.38%	6.06%	10.11%	17.35%	**22.63%**	17.10%	10.36%	6.41%	4.35%	2.70%
	6	3.52%	6.61%	10.89%	17.22%	**21.57%**	17.13%	10.82%	7.13%	4.70%	2.82%
	7	3.71%	7.02%	10.47%	16.17%	**19.16%**	16.18%	10.64%	7.35%	5.11%	3.16%
	8	4.16%	6.98%	10.71%	15.52%	**18.24%**	15.24%	10.90%	7.84%	5.38%	3.32%
	9	4.36%	7.20%	11.20%	15.37%	**17.44%**	15.18%	10.86%	8.29%	5.76%	3.47%
	10	4.54%	7.38%	10.83%	14.65%	**16.80%**	14.59%	10.89%	8.27%	6.05%	3.76%
	11	4.77%	7.82%	10.98%	14.23%	**15.91%**	14.38%	11.06%	8.50%	6.23%	4.05%
	12	5.12%	8.04%	11.20%	14.60%	**15.85%**	14.46%	11.34%	8.67%	6.58%	4.25%

Table IA.3, continued

Panel C: Subset of Funds with Low Stock-Picking Skill in Month *t*, Proxied by Low Levels of Fund Underpricing in FU Decile 1

Fund	Horizon (t+i)	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
D1 funds	1	**78.09%**	13.66%	4.19%	3.00%	1.97%	1.93%	2.04%	2.06%	1.78%	1.56%
in Month (t)	2	**68.83%**	17.08%	5.11%	3.25%	2.34%	2.05%	1.96%	1.80%	1.69%	1.82%
	3	**64.05%**	19.22%	6.53%	3.73%	2.60%	2.20%	2.05%	1.94%	1.64%	1.74%
	4	**58.02%**	19.99%	7.66%	4.40%	3.19%	2.74%	2.43%	2.05%	1.73%	1.80%
	5	**54.74%**	20.69%	8.53%	4.88%	3.50%	3.01%	2.67%	2.20%	1.75%	1.78%
	6	**53.60%**	21.31%	9.34%	5.43%	3.95%	3.19%	2.77%	2.33%	1.71%	1.85%
	7	**49.03%**	20.81%	9.49%	5.74%	4.14%	3.46%	3.10%	2.57%	2.25%	2.23%
	8	**46.36%**	20.55%	9.64%	6.14%	4.36%	3.65%	3.26%	2.71%	2.64%	2.48%
	9	**45.28%**	20.46%	9.97%	6.57%	4.62%	3.91%	3.53%	3.11%	2.67%	2.66%
	10	**42.29%**	19.77%	10.12%	6.72%	5.09%	4.24%	3.76%	3.39%	2.82%	3.07%
	11	**41.07%**	19.37%	10.58%	7.11%	5.24%	4.45%	3.88%	3.54%	2.97%	3.32%
	12	**40.75%**	19.58%	11.21%	7.33%	5.43%	4.73%	4.35%	3.59%	2.93%	3.31%

Table IA.4 Alternative Fund Performance Measures

This table assesses the robustness of our baseline results in Panel B of Table 3, with respect to alternative measures of fund performance, including the fund's monthly gross returns (adding back expenses); CAPM alpha; Carhart (1997) four-factor (FF4) alpha; the alpha of a liquidity factor model (FFL) that includes the Carhart (1997) four factors plus the liquidity factor of Pástor and Stambaugh (2003); and the alpha of a mispricing factor (FFM) that includes the Carhart (1997) four factors plus the Stambaugh and Yuan (2017) mispricing factor, with all alpha measures estimated using the fund's monthly gross returns. All regressions include style-by-month fixed effects, with standard errors clustered by fund. Numbers in parentheses are t-statistics. The 10%, 5% and 1% significance levels are denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
	RRET	CAPM	FF4	FFL	FFM
FU	0.006***	0.010***	0.002	0.001	0.002
	(2.86)	(5.52)	(0.95)	(0.69)	(1.36)
CR	−6.571***	−4.006**	−4.207***	−4.200***	−2.835**
	(−3.90)	(−2.36)	(−2.72)	(−2.73)	(−2.22)
FU×CR	**0.113*** **	**0.069** **	**0.070*** **	**0.069*** **	**0.048** **
	(4.01)	**(2.43)**	**(2.70)**	**(2.69)**	**(2.27)**
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Style x Time	Style x Time	Style x Time	Style x Time	Style x Time
Cluster	Fund	Fund	Fund	Fund	Fund
Obs.	337,211	337,205	337,205	337,205	318,243
Adj. R^2	0.79	0.22	0.08	0.09	0.14

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