Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Mutual Funds and Mispriced Stocks

Doron Avramov, Si Cheng, Allaudeen Hameed

informs
http://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Vol. 66, No. 6, June 2020, pp. 2372–2395
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Mutual Funds and Mispriced Stocks

Doron Avramov,[a,b] **Si Cheng,**[c] **Allaudeen Hameed**[d]

[a] IDC Herzliya, 4610101 Herzliya, Israel; [b] Hebrew University of Jerusalem, 9190501 Jerusalem, Israel; [c] Chinese University of Hong Kong, Shatin, Hong Kong; [d] National University of Singapore, Singapore 119245

Contact: doron.avramov@idc.ac.il (DA); sicheng@cuhk.edu.hk, https://orcid.org/0000-0002-2109-7636 (SC); allaudeen@nus.edu.sg, https://orcid.org/0000-0001-7512-5295 (AH)

Received: November 21, 2016
Revised: June 2, 2018; January 25, 2019
Accepted: January 31, 2019
Published Online in Articles in Advance: October 15, 2019

https://doi.org/10.1287/mnsc.2019.3319

Abstract. We propose a new measure of fund investment skill, *active fund overpricing* (AFO), encapsulating the fund's active share of investments, the direction of fund active bets with regard to mispriced stocks, and the dispersion of mispriced stocks in the fund's investment opportunity set. We find that fund activeness is not sufficient for outperformance: high (low) AFO funds taking active bets on the wrong (right) side of stock mispricing achieve inferior (superior) fund performance. However, high AFO funds receive higher flows during periods of high investor sentiment, when the performance–flow relation becomes weaker.

History: Accepted by Karl Diether, finance.
Funding: This work was supported by a National University of Singapore Academic Research Grant [AcRF Tier 1 Grant R-315-000-124-115] to A. Hameed.
Supplemental Material: The internet appendix is available at https://doi.org/10.1287/mnsc.2019.3319.

Keywords: mutual funds • managerial skills • mispricing

1. Introduction

Recent statistics from the Investment Company Institute show that the total net assets managed by 3,193 U.S. domestic equity mutual funds exceeded 7.4 trillion dollars as of April 2018. Funds aim to create value for their investors through their skills in stock picking and market timing (e.g., Fama 1972, Daniel et al. 1997). As mutual funds typically undertake long-only positions, stock picking skills involve identifying mispriced stocks and actively overweighting undervalued assets and underweighting (or avoiding) overpriced assets. There is also a large body of evidence in support of mispricing identified by market anomalies. For example, Stambaugh et al. (2012, 2015) and Avramov et al. (2013) show that many market anomalies extract their profitability from selling short overpriced stocks. Their findings are consistent with impediments to arbitrage such as short-sale constraints giving rise to stock prices that reflect the views of the more optimistic investors in the presence of heterogeneous beliefs about fundamental values (Miller 1977). In the context of mutual funds, Akbas et al. (2015) and Edelen et al. (2016) show that funds do not exploit predictability in the cross section of equity returns. Perhaps surprisingly, the mutual funds, in aggregate, tend to buy the stocks belonging to the short leg of anomalies and appear to exacerbate cross-sectional mispricing.[1]

In this paper, we develop a new measure of fund investment skill based on the *active* positions undertaken by funds with regard to mispriced stocks. To do this, we start with the identification of relatively overpriced stocks using the 11 well-known stock market anomalies in Stambaugh et al. (2012). The overpricing measure is based on the notion that anomalies reflect mispricing and averaging across many anomalies identifies mispriced stocks. We propose an active fund overpricing (AFO) measure as the active deviation of mutual fund investment in overpriced stocks relative to the investment weights implied by their benchmark portfolio. In other words, AFO is the difference between the fund-level investment-value-weighted average of stock-level overpricing and the average overpricing implied by the stocks in the fund's benchmark portfolio. To be precise, $AFO_{f,q}$ for fund f at time q describes the covariance between fund f's active portfolio weights (i.e., fund f's active deviation from benchmark implied weights) and overpricing of the stocks in the fund's investment universe. We hypothesize that high (low) AFO funds are associated with low (high) stock picking skills as they *actively* overweight (underweight) overpriced stocks and are expected to earn low (high) future returns as the mispricing in stocks get corrected in the next period.

We construct quarterly AFO for the actively managed U.S. equity funds that meet our data requirements for the period 1981–2010. We find that higher AFO funds display higher total net assets, higher expense ratio, and higher turnover, and they hold less liquid stocks. In addition, the cross-sectional difference in the active exposure of mutual funds to mispriced stocks is highly persistent: the propensity of a fund to actively hold overpriced stocks in a quarter continues into subsequent quarters. For example, more than half of the high (low)

AFO funds remain in the top (bottom) decile after one year.

We focus our investigation on the relation between AFO and future fund performance. We find that the cross-sectional variation in the risk-adjusted future performance of active mutual funds is significantly related to the fund's AFO. Funds in the top decile of AFO-sorted portfolios underperform those in the bottom decile by 2.27% in benchmark-adjusted return and by 1.8% in Fama–French–Carhart (FFC) four-factor-adjusted return (Fama and French 1993, Carhart 1997) per annum. The performance gap widens considerably during episodes of high market sentiment: the highest AFO funds underperform the lowest AFO funds by 4.86% in benchmark-adjusted return and by 2.56% in FFC-adjusted return per annum.

The cross-sectional negative relation between AFO and future fund returns is robust. Our main finding remains intact when we control for fund-specific characteristics (such as fund size and fund expenses) in panel and Fama and MacBeth (1973) regressions. We also consider whether there are time-series variations in the predictive relation between the fund's AFO and future performance. We do this by incorporating fund fixed effects in panel regressions of fund performance (i.e., fund returns adjusted by various performance models) on past AFO and other fund characteristics. Again, we find significant predictable time-series variations in fund performance linked to AFO: a one-standard-deviation-higher AFO predicts a reduction of benchmark-adjusted (annualized) return of 1.03% for the fund. The cross-sectional and time-series variations in the AFO–fund performance relation we document are qualitatively similar when we use different fund performance metrics.

To better understand the sources of fund skill, AFO is decomposed into the product of three components: (i) the correlation between the fund's active investment weights (i.e., relative to the fund's benchmark weights) and stock overpricing (denoted as COROP), (ii) the standard deviation of the fund's active investment weights (denoted as STDAS), and (iii) the standard deviation of stock overpricing (denoted as STDOP). High values of COROP reflect the fund's lack of skill in active portfolio management, as a positive or high correlation indicates the fund overweighting overpriced stocks relative to the benchmark. The second component, STDAS, reflects an active share in the spirit of Cremers and Petajisto (2009) and Petajisto (2013). When a fund has a high STDAS, it implies that the fund takes active positions in stocks by deviating from the benchmark portfolio weights. The final component, STDOP, defines the potential investment opportunity set encountered by the fund in terms of dispersion in stock-level overpricing. In sum, AFO integrates three elements into one unified metric: the fund's active stock picking skill, the degree of activeness of the fund, and the potential investment opportunities among mispriced stocks.

When we break down AFO into the above three components, the correlation between active fund investment weights and stock overpricing (COROP) is the strongest and most consistent predictor of fund performance. Although high STDAS funds (i.e., funds with high active share) appear to be associated positively with future performance, the association is weak. Specifically, controlling for COROP, activeness of the fund does not contain substantial predictive content for future fund returns. Finally, we find that the stock-level overpricing represented by STDOP plays a minor role in predicting fund returns. Consequently, the source of return predictability of AFO comes from the ability of funds to deviate from their benchmark weights in the direction against overpricing, beyond merely being active.

Our findings make a significant contribution to the debate in the literature on the relation between active share (which is related to our STDAS component) and fund performance. For example, Frazzini et al. (2016) argue that active share correlates with the returns on the fund's benchmark portfolio reported in Cremers and Petajisto (2009) and does not predict actual fund returns. AFO provides an improvement to the active share measure presented in Cremers and Petajisto (2009) by better isolating the fund manager's active management skill. Our findings highlight the intuition that high active share (or STDAS) funds may earn high or low future returns depending on whether the fund is underweighting (negative COROP) or overweighting (positive COROP) overpriced stocks. In other words, fund activeness is not a sufficient measure of skill, as fund managers could deviate from benchmark in the wrong direction by overweighting overpriced stocks. Hence, our AFO-based results emphasize the importance of funds being active in the right direction. Our AFO measure is also closely related to the active fundamental performance proposed by Jiang and Zheng (2018). Active fundamental performance identifies skilled managers if they overweight stocks with high cumulative abnormal returns surrounding the quarterly earnings announcement, whereas our AFO measure identifies skilled managers if they overweight underpriced stocks.

Our findings also emphasize the joint effects of stock mispricing and investor sentiment on fund performance and complement the stock-level findings in Stambaugh et al. (2012). We provide statistically and economically significant evidence that AFO is inversely related to fund performance after controlling for other predictors of fund performance including tracking error (Wermers 2003, Cremers and Petajisto 2009), industry concentration index (Kacperczyk et al. 2005), active share

(Cremers and Petajisto 2009, Petajisto 2013), and *R*-squared (Amihud and Goyenko 2013).[2] The negative AFO–fund performance relation is primarily driven by the active stock picking skill of the fund manager, which is enhanced when sentiment is high.

An alternative interpretation of the AFO–fund performance relation is that there are mispricing factors excluded from the risk-adjustment specification commonly used in the literature. If so, alpha variation across funds reflects different exposures of fund returns to mispricing factors, with high AFO funds exhibiting lower exposures. Empirical support for mispricing factors is provided by Kogan and Tian (2015) and Stambaugh and Yuan (2017). They show that characteristics-based anomalies share common return comovement and factors created from anomalies capture much of the cross-sectional variation in average stock returns. Notice also that Kozak et al. (2018) imply that alphas due to mispricing related to investor sentiment are indistinguishable from exposures to mispricing factors. Our empirical evidence indeed shows that mispricing factors play an important role in capturing the cross-sectional fund returns based on AFO. However, we find (albeit weak) relation between AFO and mispricing factor-adjusted fund performance during periods of high sentiment. An interesting implication of our findings is that the four-factor model (market, size, and two mispricing factors) proposed in Stambaugh and Yuan (2017) provides an additional metric to evaluate the performance of mutual fund managers, as actively managed mutual funds often bet on mispriced stocks.

Miller's (1977) basic assertion implies that overpriced funds are likely to be held by optimistic investors. In high sentiment periods, overpriced funds could attract additional flows as optimistic investors, buoyed by positive market sentiment, pour more money into such funds. On the other hand, prior studies have also shown that fund flows are influenced by other fund characteristics, particularly past fund returns, as investors are known to chase past performance (e.g., Chevalier and Ellison 1997) and overpriced funds are typically recent underperformers. Interestingly, we find a significant positive relation between AFO and future flows, particularly during periods of high investor sentiment. The increase in flows to high AFO funds is explained by considerably weaker sensitivity of fund flows to past performance when sentiment is high. Our findings imply that during high sentiment periods, optimistic mutual fund investors are less sensitive to past fund performance, and are more likely to invest in active funds. As the results are robust to benchmark-adjusted fund flows, the positive AFO-fund flow relationship is not driven by investor demand in a particular style or benchmark. Hence, despite poor stock picking skills, high AFO funds are able to attract flows, especially during high sentiment periods.

The rest of the paper is organized as follows. Section 2 describes the data and the construction of the variables of interest. Section 3 presents some stylized patterns of AFO. Section 4 studies the implications of active fund overpricing for future performance. Section 5 relates active fund overpricing to investor response in terms of flows. Section 6 concludes.

2. Variable Construction and Data Description

2.1. AFO Measure

We measure the degree of mutual fund-level active overpricing by aggregating the overpricing of stocks held by the fund in excess of the overpricing implied by the stocks in the fund's benchmark portfolio. Following Stambaugh et al. (2012), we construct stock-level overpricing based on 11 anomalies that survive exposures to the three factors of Fama and French (1993). Each anomaly reflects mispriced stocks and by combining the 11 anomalies, we obtain mispricing information that is common across all these anomalies (Stambaugh et al. 2015). The 11 anomalies consist of failure probability (e.g., Campbell et al. 2008, Chen et al. 2011), O-Score (Ohlson 1980, Chen et al. 2011), net stock issuance (Ritter 1991, Loughran and Ritter 1995), composite equity issuance (Daniel and Titman 2006), total accruals (Sloan 1996), net operating assets (Hirshleifer et al. 2004), momentum (Jegadeesh and Titman 1993), gross profitability (Novy-Marx 2013), asset growth (Cooper et al. 2008), return on assets (Fama and French 2006), and abnormal capital investment (Titman et al. 2004). We simply adopt the set of anomalies in Stambaugh et al. (2012) to avoid any perceived bias in the selection of anomalies.

Stock-level overpricing is constructed as follows. For each anomaly, we rank the stocks in each quarter with the highest rank indicating the most overpriced stock. Ranks are normalized to follow a $[0, 1]$ uniform distribution. For example, more overpriced stocks, or stocks with higher failure probability, higher O-Score, higher net stock issuance, higher composite equity issuance, higher total accruals, higher net operating assets, lower past six-month returns, lower gross profitability, higher asset growth, lower return on assets, and higher abnormal capital investment receive higher ranks (closer to 1). A stock's composite rank is the equal-weighted average of its ranks across all 11 anomalies, and we denote this stock-level overpricing measure for stock i in quarter q as $O_{i,q}$.

We proceed to construct fund-level active overpricing as the investment value-weighted average of stock-level overpricing minus the average overpricing implied by the stocks in the fund's benchmark portfolio.

In particular, using stocks in fund f's most recently reported portfolio holdings in quarter q, we define the active fund overpricing measure ($AFO_{f,q}$) as follows:

$$AFO_{f,q} = \sum_i \left(w_{i,f,q} - w^b_{i,f,q}\right) O_{i,q}, \tag{1}$$

where $w_{i,f,q}$ is the investment weight of stock i in fund f in quarter q and $w^b_{i,f,q}$ is the investment weight of stock i in fund f's benchmark portfolio in the same quarter.[3] Thus, our fund-level overpricing measure is related to the activeness of the fund's investment in mispriced stocks. A high $AFO_{f,q}$ implies that fund f *actively* overweights (underweights) overpriced (underpriced) stocks relative to the benchmark portfolio weights. Similarly, funds that invest less than their benchmarks in overpriced stocks display low $AFO_{f,q}$. To better understand the active fund overpricing measure, $AFO_{f,q}$ is decomposed into the product of three components:

$$\begin{aligned} AFO_{f,q} &= N_{f,q} Cov\left(w_{i,f,q} - w^b_{i,f,q}, O_{i,q}\right) \\ &= \rho\left(w_{i,f,q} - w^b_{i,f,q}, O_{i,q}\right) N_{f,q}\sigma\left(w_{i,f,q} - w^b_{i,f,q}\right)\sigma\left(O_{i,q}\right), \end{aligned} \tag{2}$$

where $N_{f,q}$ is the number of stocks in fund f's investment universe, including the stocks held by the fund and those in the fund's benchmark portfolio. All other variables are defined in Equation (1). The decomposition of the *AFO* measure is similar in spirit to the separation of the active fundamental performance metric into multiple parts in Jiang and Zheng (2018). In particular, the first component in Equation (2), $\rho(w_{i,f,q} - w^b_{i,f,q}, O_{i,q})$, measures the correlation between the benchmark-adjusted investment weight of stock i in fund f and overpricing of stock i, which we label as $COROP_{f,q}$. A positive $COROP_{f,q}$ means that the deviation of fund f's investment relative to the fund's benchmark is positively correlated with the level of stock overpricing. In other words, positive $COROP_{f,q}$ implies that fund f *actively* deviates from benchmark portfolio weights by tilting its holdings toward more overpriced stocks and away from less overpriced stocks. A negative $COROP_{f,q}$ is obtained when a fund overweights less overpriced stocks relative to the benchmark weights. Thus, a positive (negative) $COROP_{f,q}$ indicates poor (good) managerial skill with respect to picking mispriced stocks as defined by the anomalies. Hence, the $COROP_{f,q}$ component of $AFO_{f,q}$ proxies for the active stock picking skill of the fund manager.

The second component in Equation (2), $N_{f,q}\sigma(w_{i,f,q} - w^b_{i,f,q})$, measures the standard deviation of benchmark-adjusted investment weight, and is labelled as $STDAS_{f,q}$. This is similar to the active share proxy in Cremers and Petajisto (2009) and Petajisto (2013), which is defined as the absolute difference in investment weights of fund f relative to its benchmark weights. A higher $STDAS_{f,q}$ stands for greater deviation from the corresponding benchmark weights and hence more active investment. Notice that the product of the first two components (i.e., $COROP_{f,q}$ and $STDAS_{f,q}$) indicates that high active share could generate positive performance only if the activeness is in the right direction (i.e., in underweighting overpriced stocks). Otherwise, high active share could hurt performance when high active share is accompanied by positive $COROP_{f,q}$. Hence, our *AFO* measure provides an important improvement in relating fund activeness to performance as it takes into account both the fund's deviation of holdings relative to the benchmark (i.e., active share) and the direction of the bet (with regard to mispricing).[4]

The final component in Equation (2), $\sigma(O_{i,q})$, represents the cross-sectional standard deviation of stock-level overpricing among the stocks in the universe of fund f, and it is labelled as $STDOP_{f,q}$. It broadly defines the investment opportunities in terms of stock overpricing among all the stocks that mutual funds can potentially invest.

Taking together all the three components, a high AFO for a fund can be attributed to an active deviation of the fund holdings toward highly overpriced stocks (high COROP), an active investment strategy (high STDAS), and high cross-sectional variation in overpricing among stocks in the fund's investment universe (high STDOP). As noted earlier, unlike the Cremers and Petajisto (2009) measure of fund active share, AFO incorporates both the activeness of the fund (i.e., deviation from the benchmark portfolio) as well as the fund's active exposure to overpriced stocks. We investigate whether the variation in AFO proxies for managerial skill and helps to explain cross-fund differences in future performance. As the mispricing-based profit opportunities captured by the AFO measure is likely to be time-varying, we also explore if the evolution of a fund's active exposure to mispriced stocks over time predicts fund performance.

2.2. Data Sources and Sample Description

Daily and monthly common stock data are from the Center for Research in Security Prices (CRSP) database, and quarterly and annual financial statement data come from the COMPUSTAT database. We use these data to construct the 11 anomalies in Stambaugh et al. (2012). The details on the construction of each firm-specific variables underlying the 11 market anomalies are described in Appendix A. Most anomalies are constructed on an annual basis, whereas the failure probability, O-score, and return on assets are computed quarterly, and momentum is updated monthly. For anomalies based on information from financial statements, we use the fiscal year-end but consider the accounting variables as observable in June of the next calendar year.

We obtain quarterly institutional equity holdings from the Thomson-Reuters Mutual Fund Holdings database. The database contains quarter-end security holding information for all registered mutual funds that report their holdings to the U.S. Securities and Exchange Commission. We match the holdings database to the CRSP mutual fund database, which reports monthly net-of-fee returns and total net assets (TNA). We focus on U.S. equity mutual funds and include all CRSP/Thomson-Reuters-merged general equity funds that have one of the following Lipper objectives: "EI," "EMN," "G," "GI," "I," "LSE," "MC," "MR," or "SG." Although two of these fund objectives, "EMN" and "LSE," may involve long-short trading strategies, our main findings are unaffected by excluding these two categories of funds. We eliminate index funds by deleting those whose name includes any of the following strings: "Index," "Ind," "Ix," "Indx," "S&P," "500," "Dow," "DJ," "Nasdaq," "Mkt," "Barra," "Wilshire," and "Russell." In unreported results, we confirm that our findings are robust to excluding the closet indexers, defined as funds with active share below 60%, following Cremers and Petajisto (2009) and Cremers et al. (2016). We consolidate multiple share classes into portfolios by adding together share-class TNA and by value-weighting share-class characteristics (e.g., returns, fees) based on lagged share-class TNA. Similar to Elton et al. (1996) and Amihud and Goyenko (2013), funds are required to have TNA of at least USD15 million. We consider Lipper objectives from CRSP to define the benchmark of the mutual funds, and our findings are robust to using a Morningstar 3×3 style box to define fund style groups. We conduct our analyses accounting for similarities among funds within the same fund benchmark. Whenever available, data on the index holdings of the Russell indexes and S&P indexes come from the FTSE Russell and COMPUSTAT, respectively. We employ the holdings from index funds as a proxy for index holdings for the remaining indexes and sample periods (e.g., Jiang and Sun 2014, Jiang and Zheng 2018). Our final sample consists of 1,648 unique actively managed equity mutual funds and covers the period from 1981 to 2010. On average, our sample includes 442 funds per quarter.

Our *AFO* measure at the fund-level mirrors the selection of mispriced stocks by funds and, hence, reflects the stock picking skills of fund managers. To control for the effects of fund characteristics that may influence our findings, we construct a list of fund-specific variables, including log(*Fund TNA*), defined as the logarithm of the fund TNA; *Expense Ratio*, defined as the annualized fund expense ratio; *Turnover*, defined as the annualized fund turnover ratio; log(*Fund Age*), defined as the logarithm of the age of the fund; log(*Manager Tenure*), defined as the logarithm of manager tenure, and log(*Fund Illiquidity*), defined as the logarithm of the illiquidity of stocks in a fund's holding portfolio. Fund attributes formed based on stock characteristics (e.g., illiquidity) are computed as the investment value-weighted average of stock characteristics. Furthermore, to ensure that our *AFO* measure is different from other managerial skill proxies documented in the literature, our empirical investigations also controls for *Active Share* (Cremers and Petajisto 2009, Petajisto 2013),[5] *R-square* (Amihud and Goyenko 2013), *Industry Concentration Index* (Kacperczyk et al. 2005), and *Tracking Error* (Wermers 2003, Cremers and Petajisto 2009). Detailed descriptions of all variables are provided in Appendix A.

Table 1 provides the summary statistics of stocks sorted into deciles based on the overpricing measure. It is apparent that stock overpricing is negatively related to future performance: stocks in the most overpriced decile earn about 2% less per month than the least overpriced stocks, over the next quarter. In addition, overpriced stocks are more illiquid, less covered by analysts, have higher idiosyncratic volatility, and record lower market capitalization. The most overpriced stocks display characteristics that are consistent with high short-sale constraints and difficulty to arbitrage (see, e.g., Stambaugh et al. 2012, 2015).

Interestingly, mutual funds tend to hold less overpriced stocks. On the one hand, mutual funds hold only 6.3% of stocks in the highest decile of overpriced stocks, significantly less than the unconditional expected holdings of 10%. On the other hand, mutual fund ownership of the less overpriced stocks is slightly above 10% in the lowest few overpricing deciles. This accords with the finding that mutual funds have a significant preference toward large, liquid stocks (Falkenstein 1996). Whereas mutual fund ownership monotonically diminishes with stock overpricing, mutual funds are positively exposed to overpriced stocks in their portfolios (see, e.g., Edelen et al. 2016).

3. Stylized Patterns of Active Fund Overpricing

Table 2 reports the characteristics of mutual funds with varying propensity to actively hold overpriced stocks. We sort mutual funds into 10 groups based on the fund's average AFO at the end of each quarter q and report average fund characteristics during quarter q and subsequent quarters.

As laid out in Equation (2), AFO can be decomposed into stock picking skill (COROP), the activeness of the fund (STDAS), and the diversity of the investment opportunity set (STDOP). Table 2 shows a U-shaped pattern in STDAS: the funds in the extreme AFO deciles exhibit high active share. On the other

Table 1. Stock Overpricing and Stock Characteristics

	Overpricing and stock characteristics								
Rank of overpricing	$Overpricing_q$	Stock $Return_{q+1}$	Market $Share_q$	log(Stock $Price)_q$	log(Stock $Size)_q$	log(Stock $Illiquidity)_q$	Mutual Fund $Ownership_q$	Analyst $Coverage_q$	$IdioVol_q$
Low	0.295	1.968	0.252	3.007	5.794	6.043	10.549	3.201	2.002
2	0.368	1.729	0.181	2.859	5.655	6.251	10.629	3.093	2.160
3	0.412	1.583	0.133	2.733	5.485	6.463	10.522	2.925	2.281
4	0.447	1.590	0.111	2.594	5.284	6.720	10.233	2.797	2.437
5	0.480	1.515	0.089	2.449	5.078	7.004	9.832	2.593	2.625
6	0.513	1.386	0.073	2.313	4.892	7.282	9.413	2.406	2.814
7	0.547	1.263	0.060	2.175	4.718	7.512	8.908	2.266	2.987
8	0.586	1.010	0.046	2.021	4.557	7.743	8.354	2.087	3.190
9	0.634	0.827	0.035	1.815	4.366	7.990	7.715	1.908	3.475
High	0.726	−0.048	0.020	1.474	4.049	8.405	6.331	1.592	4.021
LMH	−0.431	2.016***	0.232***	1.533***	1.745***	−2.362***	4.219***	1.609***	−2.019***
		(7.11)	(16.26)	(23.46)	(15.77)	(−13.75)	(7.81)	(9.00)	(−14.43)

Notes. Stocks are sorted into deciles according to lagged overpricing in quarter q. This table reports, for each decile portfolio, the average overpricing (*Overpricing*), log(*Stock Price*), log(*Stock Size*), log(*Stock Illiquidity*), mutual fund ownership, analyst coverage, idiosyncratic volatility, and the market share represented by each decile portfolio in formation quarter q, as well as the average stock return in the following quarter $q+1$ over the entire sample period from 1981 to 2010. The row "LMH" reports the difference in values between low and high overpricing portfolios ("the bottom 10% − the top 10%"). Appendix A provides the detailed definitions of each variable. Newey–West adjusted t-statistics (Newey and West 1987) are shown in parentheses.

*, **, and ***Significance at the 10%, 5%, and 1% levels, respectively.

hand, COROP monotonically increases with AFO. Although both high and low AFO funds tend to actively deviate from the benchmark portfolio weights, high (low) AFO funds have high (low) active exposure to overpriced stocks, and hence their active bets are in the wrong (right) direction of stock mispricing. Consequently, the activeness of low AFO funds corresponds to the managerial stock picking skill in identifying underpriced stocks and taking active positions in these stocks. High AFO funds, by contrast, actively overweight overpriced stocks, and this active deviation from the benchmark does not suggest better skill. This observation further reinforces the importance of differentiating the quality of active management (i.e., betting on the right direction of mispricing, proxied by COROP) from the quantity of active management (proxied by STDAS). The third component, STDOP, is marginally higher in the extreme deciles, suggesting that there is smaller variation in the universe of mispriced stocks available to these funds. Moreover, we find a low unconditional correlation of −6% between STDOP and AFO.

The propensity of a fund to actively hold overpriced stocks continues into subsequent quarters, indicating persistence in the active exposure of funds to overpricing in the stocks held. The average active fund overpricing across the deciles is similar in one quarter or one year ahead. Specifically, the difference in the average AFO of funds in the lowest and the highest AFO deciles after one (four) quarter(s) is highly significant at −11.2% (−9%). In unreported results, we find that more than 50% of the high (low) AFO funds remain in the top (bottom) AFO decile one year later.

As shown in Table 2, high AFO funds also display relatively higher total net assets, higher expense ratio, higher turnover, and lower stock liquidity, yet they have similar age and manager tenure as other funds. Unconditionally, there is an insignificant difference in subsequent flows between the most and the least actively overpriced funds. Unreported results show that the correlation between AFO and overpricing of the benchmark portfolio is −0.3, reinforcing that AFO is different from overpricing in the benchmark portfolio.

The univariate findings in Table 2 are further supported by multivariate Fama-MacBeth (1973) regressions of the fund's *AFO* on its lagged value as well as a set of control variables, including lag(*Fund Return*), lag(*Fund Flow*), log(*Fund TNA*), *Expense Ratio*, *Turnover*, log(*Fund Age*), log(*Manager Tenure*), and log(*Fund Illiquidity*). As reported in Table 3, funds with high active exposure to overpriced stocks display low past fund returns and are larger, have high expenses and turnover, and hold more illiquid stocks. Controlling for these fund characteristics, there is strong persistence in active fund overpricing in both uarterly and annual frequencies. The quarterly (annual) correlation of a fund's AFO with its lagged value is highly significant at 0.895 (0.719) in Model 1 (Model 6). We also examine the persistence in overpricing focusing on funds in the highest and in the lowest AFO decile. As reported in Models 4 and 9, the quarterly (annual) persistence in AFO exists for both deciles.

In Models 3 and 8, we observe stronger persistence among funds with less turnover, implying that funds that trade more often tend to decrease the persistence

Table 2. Active Fund Overpricing and Other Fund Characteristics

	Active fund overpricing and other fund characteristics												
Rank of AFO	AFO_q	$COROP_q$	$STDAS_q$	$STDOP_q$	log(*Fund TNA*)$_q$	*Expense Ratio*$_q$	*Turnover*$_q$	log(*Fund Age*)$_q$	log(*Manager Tenure*)$_q$	log(*Fund Illiquidity*)	AFO_{q+1}	*Fund Flow*$_{q+1}$	AFO_{q+4}
Low	−0.043	−0.091	4.528	0.114	5.360	1.082	0.588	5.243	4.475	3.752	−0.037	0.305	−0.027
2	−0.019	−0.052	3.805	0.111	5.506	1.012	0.616	5.286	4.398	3.254	−0.016	0.256	−0.009
3	−0.009	−0.027	3.492	0.111	5.766	0.969	0.623	5.284	4.363	3.116	−0.007	0.229	−0.003
4	−0.001	−0.004	3.441	0.111	5.897	0.961	0.623	5.303	4.387	3.177	0.001	0.277	0.002
5	0.006	0.017	3.429	0.111	5.913	0.971	0.679	5.331	4.367	3.166	0.007	0.129	0.006
6	0.014	0.038	3.641	0.111	5.889	0.987	0.737	5.336	4.356	3.362	0.014	0.203	0.013
7	0.022	0.059	3.784	0.111	5.814	1.018	0.772	5.293	4.381	3.553	0.022	0.478	0.020
8	0.032	0.081	3.938	0.111	5.883	1.032	0.791	5.230	4.360	3.738	0.031	0.265	0.026
9	0.047	0.106	4.287	0.112	5.792	1.119	0.807	5.164	4.359	4.077	0.043	0.379	0.036
High	0.082	0.158	4.990	0.112	5.649	1.210	0.792	5.151	4.459	4.727	0.074	0.336	0.064
LMH	−0.125	−0.250***	−0.461***	0.002**	−0.289***	−0.128***	−0.204***	0.092	0.017	−0.974***	−0.112***	−0.031	−0.090***
		(−49.53)	(−4.69)	(2.51)	(−2.81)	(−4.08)	(−7.40)	(1.27)	(0.45)	(−5.30)	(−32.72)	(−0.18)	(−24.51)

Notes. Mutual funds are sorted into deciles according to lagged overpricing in quarter q. This table reports, for each decile portfolio, the average active fund overpricing (AFO) and its three components, log(*Fund TNA*), *Expense Ratio*, *Turnover*, log(*Fund Age*), log(*Manager Tenure*), and log(*Fund Illiquidity*) in formation quarter q, the AFO and fund flow in the following quarter $q + 1$, as well as the AFO in quarter $q + 4$ over the entire sample period from 1981 to 2010. The row "LMH" reports the difference in values between low and high overpricing portfolios ("the bottom 10% – the top 10%"). Appendix A provides the detailed definitions of each variable. Newey–West adjusted t-statistics (Newey and West 1987) are shown in parentheses.

*, **, and ***Significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Persistence of Active Fund Overpricing

	Active fund overpricing (in %) regressed on lagged active fund overpricing (in %)									
	Quarter $q-1$					Quarter $q-4$				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
AFO	0.895***	0.878***	0.910***			0.719***	0.673***	0.736***		
	(106.76)	(98.76)	(104.42)			(33.60)	(29.32)	(34.09)		
Dummy (Underpricing)				−4.623***	−4.713***				−3.614***	−3.870***
				(−23.06)	(−19.56)				(−14.81)	(−13.39)
Dummy (Overpricing)				5.547***	5.986***				4.482***	5.044***
				(27.51)	(27.65)				(21.93)	(24.27)
AFO × *Turnover*			−0.049***					−0.096***		
			(−4.37)					(−4.95)		
Dummy (Underpricing) × *Turnover*					0.116					0.310
					(0.44)					(1.06)
Dummy (Overpricing) × *Turnover*					−0.514***					−0.772***
					(−3.43)					(−3.61)
lag(*Fund Return*)		−0.081***	−0.075***	−0.220***	−0.220***		−0.318***	−0.309***	−0.329***	−0.330***
		(−3.27)	(−3.23)	(−4.48)	(−4.54)		(−6.04)	(−6.23)	(−4.96)	(−4.99)
lag(*Fund Flow*)		0.021***	0.021***	0.023**	0.023**		0.039***	0.041***	0.034***	0.033***
		(4.37)	(4.27)	(2.49)	(2.44)		(4.05)	(4.07)	(3.11)	(3.05)
log(*Fund TNA*)		0.027***	0.027***	0.159***	0.161***		0.101***	0.105***	0.193***	0.197***
		(2.74)	(2.72)	(4.04)	(4.06)		(3.49)	(3.44)	(4.41)	(4.36)
Expense Ratio		0.129**	0.132**	0.511***	0.536***		0.296**	0.322**	0.600***	0.642***
		(2.24)	(2.21)	(4.22)	(4.15)		(2.12)	(2.21)	(3.84)	(3.93)
Turnover		0.088***	0.173***	0.384***	0.449***		0.207***	0.388***	0.427***	0.476***
		(3.61)	(4.02)	(6.56)	(7.26)		(3.32)	(4.52)	(6.25)	(7.24)
log(*Fund Age*)		−0.017	−0.013	−0.113	−0.113		−0.041	−0.041	−0.097	−0.103
		(−0.75)	(−0.55)	(−1.59)	(−1.54)		(−0.73)	(−0.76)	(−1.15)	(−1.19)
log(*Manager Tenure*)		0.007	0.012	−0.025	−0.021		0.005	0.021	−0.027	−0.014
		(0.44)	(0.73)	(−0.58)	(−0.49)		(0.13)	(0.56)	(−0.54)	(−0.27)
log(*Fund Illiquidity*)		0.050***	0.051***	0.268***	0.266***		0.181***	0.176***	0.331***	0.329***
		(3.60)	(3.74)	(6.23)	(6.26)		(4.98)	(4.99)	(6.16)	(6.21)
Intercept	0.131***	−0.233	−0.343**	−0.655	−0.733*	0.322***	−0.894**	−1.086**	−1.212**	−1.330**
	(4.31)	(−1.66)	(−2.09)	(−1.57)	(−1.70)	(3.52)	(−2.08)	(−2.38)	(−2.07)	(−2.23)
R-squared	0.803	0.825	0.829	0.589	0.596	0.524	0.591	0.599	0.459	0.469
Obs.	51,751	51,751	51,751	51,751	51,751	51,751	51,751	51,751	51,751	51,751

Notes. In this table, Models 1–5 present the results of the following quarterly Fama-MacBeth (1973) regressions, as well as their corresponding Newey–West adjusted *t*-statistics (Newey and West 1987):

$$AFO_{f,q} = \alpha_0 + \beta_1 AFO_{f,q-1} + cM_{f,q-1} + e_{f,q},$$

where $AFO_{f,q}$ is the active fund overpricing of fund f in quarter q, and the vector M stacks all other control variables, including lag(*Fund Return*), lag(*Fund Flow*), log(*Fund TNA*), *Expense Ratio*, *Turnover*, log(*Fund Age*), log(*Manager Tenure*), and log(*Fund Illiquidity*); $AFO_{f,q-1}$ can be further replaced with two dummy variables, $Dummy(Underpricing)_{f,q-1}$ (takes a value of 1 if the $AFO_{f,q-1}$ is in the bottom decile across all funds in that quarter and 0 otherwise) and $Dummy(Overpricing)_{f,q-1}$ (takes a value of 1 if the $AFO_{f,q-1}$ is in the top decile across all funds in that quarter and 0 otherwise). Models 6–10 report similar regression parameters of the following quarterly Fama-MacBeth (1973) regressions:

$$AFO_{f,q} = \alpha_0 + \beta_1 AFO_{f,q-4} + cM_{f,q-1} + e_{f,q},$$

where all variables are defined as above. Appendix A provides detailed definitions for each variable.
*, **, and ***Significance at the 10%, 5%, and 1% levels, respectively.

in AFO. Fund turnover here is based on the annual fund turnover ratio reported by the funds. The diminishing persistence in AFO for funds that turn over their holdings comes from the highest AFO funds. By contrast, for the low AFO decile funds, the persistence in fund overpricing is unaffected by fund turnover (see Models 5 and 10). The finding that high trading by funds, on average, lowers AFO is consistent with the evidence in Pástor et al. (2017) that active funds exhibit an ability to identify time-varying profit opportunities and adjust their trading activities to take advantage of such opportunities, especially when mispricing is more likely. In sum, the propensity of mutual funds to actively overweight overpriced stocks relative to the benchmark is correlated with several prominent fund characteristics and is highly persistent.

4. Active Fund Overpricing and Fund Performance

In this section, we conduct a comprehensive set of tests to examine whether active overpricing by mutual funds (AFO) predicts future fund performance. There are several reasons why a fund's AFO may be unrelated to its future performance. First, the results in Tables 1 and 2 show that cross-fund differences in overpricing are smaller than the cross-sectional variation in stock overpricing measures; that is, mutual funds have lower exposure to overpriced stocks. Second, the aggregate mutual fund exposure to stock overpricing document by Edelen et al. (2016) and others may be driven by fund passive holdings (i.e., benchmark index holdings). Third, fund managers may respond to stock overpricing by dynamically adjusting their holdings to mitigate the effects of stock overpricing. On the other hand, if AFO is related to fund managers' ability to select stocks, AFO should predict the fund performance in terms of risk-adjusted, benchmark-adjusted, and style-adjusted fund returns. Hence, the relation between active overpricing and managerial skill is an empirical question that we explore in what follows. We start with investigating the cross-sectional relation between AFO and future fund performance. Because a fund may also dynamically adjust the active exposure to overpriced stocks, we also investigate (in panel regressions) if there are significant within-fund time-series variations in the AFO–performance relation.

4.1. Portfolio Analyses

Our portfolio approach relies on sorting mutual funds into deciles according to lagged AFO in month m, and it examines the value-weighted (i.e., lagged fund TNA-weighted) average (net-of-fee) fund return realized in month $m + 1$. In unreported results, we obtain qualitatively and quantitatively similar returns when funds in each decile are equally weighted. We assess fund performance through fund returns, benchmark-adjusted fund returns (BMK-adjusted), style-adjusted returns, factor-adjusted returns per the CAPM and the FFC four-factor model, as well as characteristic-adjusted returns per the DGTW model of Daniel et al. (1997). These performance adjustment models are representative of those used in the literature on mutual fund performance evaluation. The adjustment of fund returns for exposure to size and value risk factors or characteristics is advocated in Fama and French (1993) and Daniel et al. (1997), among others. The adjustment of fund returns for price momentum effects comes from the evidence in Carhart (1997). We do not take a stand on whether these factors or characteristics arise from rational or behavioral sources. As argued in Kozak et al. (2018), it is difficult to distinguish between risk and behavioral sources of these factors (see also Section 4.4). More important, we consider a range of models in our assessment of the performance of funds.

Table 4 reports the average fund (abnormal) return in each AFO decile as well as the differential return between the least and the most overpriced funds ("LMH"). It is evident from panel A of Table 4 that the highest AFO funds underperform the lowest AFO funds by an economically significant 0.194% per month (or 2.33% per annum) in raw return over the sample period from 1981 to 2010.[6] Although differences in fund performance could result from differential performance of the benchmark index associated with the fund, we find that this is not the case. The highest AFO funds generate a benchmark-adjusted return that is 2.27% per annum lower than the funds with the lowest AFO. We also obtain similar differential fund return in excess of the fund-style portfolio returns of about 2.1% per annum between the extreme AFO deciles. We also consider several alternative risk-adjustment models commonly used in the literature on mutual fund performance evaluation. When future fund performance is measured by the CAPM-adjusted returns, the difference in returns between funds in the lowest and highest AFO deciles increases to an economically larger magnitude of 3.56% per annum. Considering the FFC four-factor model, the return spread between the two extreme deciles is significant at 1.8% per year. The only exception is that when fund returns are adjusted using the DGTW characteristics model, the difference in the cross-sectional fund returns becomes insignificant.

In Figure 1, we present the performance effects associated with low and high AFO fund deciles as well as the difference in the returns between low and high AFO funds in subsequent months, from month $m + 1$ to month $m + 12$. The figure shows that funds in the highest AFO decile continue to perform poorly in the subsequent months. The benchmark-adjusted returns displayed in Figure 1 are significantly negative for the high AFO decile in the months up to $t + 8$. For the lowest AFO decile, we observe continued positive benchmark-adjusted returns in the months up to $t +$ 10. The difference in benchmark-adjusted returns between the low and the high AFO deciles is positive in all 12 months. Hence, the evidence suggests a drift in the performance of low minus high AFO fund portfolio, which decays slowly over the 12-month period.

In sum, we find evidence of unconditional cross-sectional variation in fund performance that is

Table 4. Mutual Fund Returns Sorted by Active Fund Overpricing

Rank of AFO	*Fund Return*	*BMK-adj. Return*	*Style-adj. Return*	*DGTW-adj. Return*	*CAPM-adj. Return*	*FFC-adj. Return*
Panel A. Returns to investment strategies sorted by active fund overpricing (1981–2010)						
Low	0.964***	0.089	0.093	0.078*	0.130*	0.048
	(4.15)	(1.38)	(1.59)	(1.66)	(1.86)	(0.79)
2	0.892***	0.028	0.046	0.062*	0.032	−0.021
	(3.69)	(0.67)	(1.02)	(1.66)	(0.74)	(−0.49)
3	0.882***	0.016	0.018	0.045	0.018	−0.034
	(3.61)	(0.44)	(0.42)	(1.33)	(0.39)	(−0.96)
4	0.872***	0.036	0.044	0.012	0.016	−0.032
	(3.61)	(0.96)	(0.93)	(0.33)	(0.32)	(−0.80)
5	0.831***	−0.028	−0.021	−0.010	−0.033	−0.059
	(3.42)	(−0.76)	(−0.44)	(−0.28)	(−0.69)	(−1.27)
6	0.895***	0.040	0.026	0.083**	0.006	−0.038
	(3.47)	(1.20)	(0.51)	(2.17)	(0.12)	(−0.91)
7	0.846***	−0.009	−0.019	0.022	−0.041	−0.065
	(3.20)	(−0.25)	(−0.40)	(0.54)	(−0.91)	(−1.44)
8	0.863***	−0.009	−0.019	0.035	−0.032	−0.037
	(3.23)	(−0.21)	(−0.40)	(0.80)	(−0.61)	(−0.70)
9	0.822***	−0.033	−0.034	−0.016	−0.077	−0.047
	(3.01)	(−0.69)	(−0.65)	(−0.34)	(−1.14)	(−0.67)
High	0.770***	−0.100*	−0.081	0.018	−0.167**	−0.102
	(2.61)	(−1.79)	(−1.44)	(0.36)	(−2.36)	(−1.52)
LMH	0.194*	0.189*	0.175*	0.060	0.297***	0.150*
	(1.73)	(1.80)	(1.83)	(0.87)	(2.97)	(1.83)
Panel B. Returns to investment strategies sorted by active fund overpricing (high sentiment)						
Low	1.096***	0.208**	0.239***	0.189***	0.302***	0.141*
	(3.65)	(2.11)	(2.66)	(2.70)	(3.35)	(1.94)
2	0.944***	0.050	0.111*	0.121**	0.108*	0.034
	(2.79)	(0.90)	(1.73)	(2.35)	(1.74)	(0.58)
3	0.934***	0.028	0.057	0.110**	0.099	0.007
	(2.71)	(0.53)	(0.88)	(2.23)	(1.35)	(0.11)
4	1.004***	0.129**	0.175***	0.066	0.175**	0.082
	(2.98)	(2.58)	(2.78)	(1.24)	(2.35)	(1.36)
5	0.876**	−0.012	0.012	0.045	0.033	−0.033
	(2.56)	(−0.27)	(0.19)	(0.82)	(0.47)	(−0.48)
6	0.986***	0.094*	0.145*	0.163***	0.122*	0.007
	(2.69)	(1.73)	(1.91)	(2.67)	(1.74)	(0.11)
7	0.873**	0.008	0.029	0.060	0.020	−0.037
	(2.39)	(0.15)	(0.50)	(1.01)	(0.29)	(−0.51)
8	0.866**	−0.011	0.015	0.085	0.004	−0.022
	(2.37)	(−0.20)	(0.21)	(1.38)	(0.06)	(−0.28)
9	0.736**	−0.082	−0.075	−0.023	−0.121	−0.053
	(2.03)	(−1.33)	(−1.12)	(−0.34)	(−1.33)	(−0.54)
High	0.702*	−0.197**	−0.105	0.006	−0.205*	−0.071
	(1.68)	(−2.27)	(−1.17)	(0.08)	(−1.82)	(−0.66)
LMH	0.394**	0.405**	0.344**	0.184*	0.507***	0.213*
	(2.07)	(2.43)	(2.21)	(1.67)	(3.19)	(1.68)

attributable to the fund's active exposure to overpricing: high AFO funds underperform low AFO funds.[7] Next, we examine whether the return differential between the AFO sorted funds varies with investor sentiment and find economically larger differences (ranging from 2.21% to 6.08% per year) during episodes of high sentiment.

4.1.1. The Effect of Investor Sentiment. Stambaugh et al. (2012) document that the stock-level relation between overpricing and future returns varies over time. Specifically, overpricing based on market anomalies exhibits a stronger negative relation to future returns during high sentiment periods. They attribute the sentiment effect to binding short-sale constraints, which

Table 4. (Continued)

Rank of AFO	*Fund Return*	*BMK-adj. Return*	*Style-adj. Return*	*DGTW-adj. Return*	*CAPM-adj. Return*	*FFC-adj. Return*
Panel C. Returns to investment strategies sorted by active fund overpricing (low sentiment)						
Low	0.832**	−0.030	−0.052	−0.033	−0.067	−0.076
	(2.34)	(−0.41)	(−0.81)	(−0.63)	(−0.92)	(−1.10)
2	0.840**	0.005	−0.019	0.002	−0.049	−0.062
	(2.43)	(0.09)	(−0.34)	(0.04)	(−0.94)	(−1.15)
3	0.830**	0.004	−0.022	−0.020	−0.072	−0.071*
	(2.37)	(0.09)	(−0.39)	(−0.44)	(−1.58)	(−1.81)
4	0.740**	−0.056	−0.087	−0.042	−0.152***	−0.153***
	(2.13)	(−1.19)	(−1.44)	(−0.93)	(−3.28)	(−3.54)
5	0.787**	−0.043	−0.053	−0.066	−0.101	−0.097
	(2.31)	(−0.76)	(−0.82)	(−1.30)	(−1.52)	(−1.56)
6	0.805**	−0.014	−0.093*	0.002	−0.112**	−0.119***
	(2.22)	(−0.42)	(−1.70)	(0.06)	(−2.56)	(−2.85)
7	0.818**	−0.025	−0.066	−0.016	−0.111**	−0.108**
	(2.15)	(−0.58)	(−0.99)	(−0.27)	(−2.19)	(−2.08)
8	0.859**	−0.006	−0.053	−0.015	−0.074	−0.089
	(2.24)	(−0.11)	(−0.89)	(−0.27)	(−1.11)	(−1.37)
9	0.908**	0.016	0.008	−0.009	−0.044	−0.047
	(2.25)	(0.23)	(0.11)	(−0.14)	(−0.51)	(−0.54)
High	0.838**	−0.003	−0.057	0.030	−0.124	−0.123
	(2.05)	(−0.05)	(−0.87)	(0.51)	(−1.42)	(−1.52)
LMH	−0.006	−0.027	0.006	−0.064	0.057	0.047
	(−0.05)	(−0.24)	(0.06)	(−0.84)	(0.65)	(0.55)

Notes. Mutual funds are sorted into deciles according to lagged active fund overpricing (AFO) in month m. Panel A reports the month $m+1$ (value-weighted) return for each decile portfolio as well as the strategy of going long (short) the one-month underpriced (overpriced) funds ("LMH") over the entire sample period from 1981 to 2010. Fund returns are further adjusted by the benchmark return of funds, the Morningstar style return of funds, the Daniel et al. (1997) model, CAPM, and FFC model. Panels B and C report similar statistics in the subperiod when investor sentiment is high (above median) and low (below median) in month m, respectively. Appendix A provides the detailed definition of each variable. Newey-West adjusted t-statistics (Newey and West 1987) are shown in parentheses.

*, **, and ***Significance at the 10%, 5%, and 1% levels, respectively.

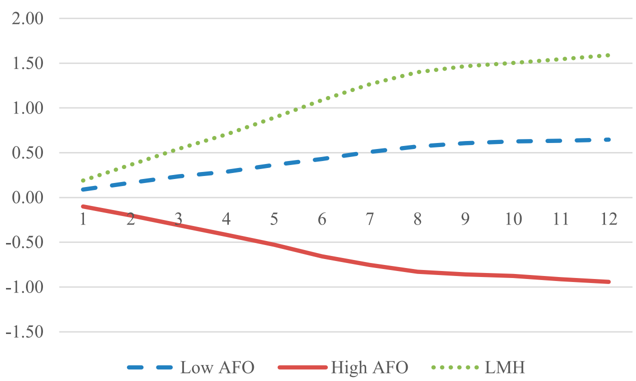
are especially at work during episodes of high investor sentiment. Also, the argument in Miller (1977) predicts that overvaluation prevails during high sentiment periods when investors may disagree about fundamental valuations and short-sale constraints bind. Consequently, we examine whether the mutual fund AFO–performance relation also depends on the state of investor sentiment. If individual mutual funds deviate from the benchmark portfolio weights by overweighting (underweighting) more overpriced stocks, this active strategy is likely to have a stronger negative (positive) effect on future fund performance when the market as a whole is overpriced. We thus conjecture that in periods of high (low) investor sentiment, there is stronger (weaker) cross-sectional relation between AFO and fund performance.

To examine the impact of investor sentiment on the AFO–fund performance relation, we split the sample into high (above-median) and low (below-median) sentiment periods based on the Baker and Wurgler (2006, 2007) investor sentiment index.[8] Panels B and C of Table 4 report the findings. Evidently, AFO predicts fund performance only during high sentiment periods. Following high sentiment periods, the most overpriced funds underperform the least overpriced funds by 4.73% (4.86%, 4.13%) per year in raw (benchmark-adjusted, style-adjusted) return. The DTGW-adjusted return difference between funds with high and low AFO is now significant at 2.21% per annum in high sentiment periods. Furthermore, when fund returns are adjusted using the CAPM, the annual return differential between the low and the high AFO deciles increases to a high 6.08%. By contrast, there is no difference in the performance of funds with high and low AFO following low sentiment periods across all fund performance metrics.[9] The results here are consistent with the notion that taking active positions in mispriced stocks is less likely to predict performance when the investor sentiment is low.

4.2. Regression Analyses

To further examine the relation between AFO and future fund performance, we employ multivariate regressions that allow us to control for fund characteristics that might also influence fund performance. By including fund-specific variables in the regressions, we ensure that these variables do not fully explain the AFO–performance relation we document. Following the extant literature, the

Figure 1. (Color online) Mutual Fund Cumulative Returns and Active Fund Overpricing



Notes. Mutual funds are sorted into deciles according to lagged AFO in month *m*. This figure plots the (value-weighted) cumulative benchmark-adjusted return for the top decile portfolio ("High AFO"), the bottom decile portfolio ("Low AFO"), as well as the strategy of going long (short) the one-month underpriced (overpriced) funds ("LMH") from month $m+1$ to month $m+12$ over the entire sample period from 1981 to 2010.

regression includes the following set of lagged fund characteristics as control variables: lag(*Fund Flow*), log(*Fund TNA*), *Expense Ratio*, *Turnover*, log(*Fund Age*), log(*Manager Tenure*), and log(*Fund Illiquidity*). We estimate the following panel regression:

$$Perf_{f,q} = \alpha_0 + \beta_1 AFO_{f,q-1} + cM_{f,q-1} + e_{f,q}, \qquad (3)$$

where $Perf_{f,q}$ is the performance of fund *f* in quarter *q*, $AFO_{f,q-1}$ is the active fund overpricing measure, and the vector *M* stacks all the fund-specific characteristics listed above as control variables. In our base analyses, we use three measures of fund performance ($Perf_{f,q}$): total fund returns, benchmark-adjusted returns, and FFC-adjusted returns.[10]

We start with panel regression estimate of the model in Equation (3) with quarter and fund fixed effects to account for the time-series as well as fund-specific variation in aggregate fund returns (see Table 5). Allowing for fund fixed effects enables the evaluation of the time-series variation in the active investment weights of funds in mispriced stocks, capturing an additional dimension of the effect of within-fund time-series variation in AFO on fund performance. The standard errors are clustered at both fund and year levels to address the across-time and across-fund correlations in the regression residuals.

We also perform a series of robustness checks in Section 4.3 with regard to model specification, estimation method, and fund performance measures. Specifically, we consider panel regression models without fund fixed effects and Fama-MacBeth (1973) regressions to focus only on the cross-sectional relation between AFO and future fund performance, similar in spirit to the portfolio analyses in the above subsection. Finally, we explore the sensitivity of the findings to other metrics to adjust for fund performance. As a preview, our main findings on the relation between AFO and future fund performance are robust across all these variations.

4.2.1. Time-Series Regression Analyses. As presented in Table 5, AFO is negatively related to future fund performance, and this time-series relation is significant for all fund performance measures and regression specifications. Focusing on Models 1, 5, and 9, AFO has a slope coefficient ranging between −1.041 and −2.528 across the three fund performance measures; all of these are statistically significant. To gauge the economic magnitude of the relation between AFO and future fund performance, a one-standard-deviation increase in AFO reduces the annualized raw (benchmark-adjusted, FFC-adjusted) fund returns by an economically significant 1.06% (1.03%, 0.44%) after controlling for fund characteristics.[11] The slope coefficients corresponding to the fund characteristics are generally consistent with those reported in the literature. For example, fund performance is negatively related to lagged fund size (Wermers 2000, Chen et al. 2004) and positively related to lagged stock illiquidity (Idzorek et al. 2012, Ibbotson et al. 2013), and these findings are robust to alternative fund performance measures (see Models 1–12 in Table 5). The fund expense ratio also affects fund performance in some regression specifications. More important, the predictive effect of AFO on mutual fund performance is robust to the inclusion of these fund characteristics and across different performance models.

As illustrated in Equation (2), AFO can be broken down into three components: stock picking skill (COROP), the active share of the fund (STDAS), and the potential investment opportunity set reflected in the stock-level overpricing (STDOP). Given that STDOP lacks cross-sectional variation as demonstrated in Table 2, we reestimate the regression in Equation (3) by replacing AFO with its first two components and report the results in Models 2, 6, and 10 in Table 5. We find that COROP is consistently an important contributor to the negative return predictability of AFO, with significant negative slope coefficients of −0.868 to −0.4 across all performance measures. The effect is economically large: a one-standard-deviation-higher COROP reduces annualized raw (benchmark-adjusted, FFC-adjusted) fund returns by 0.82% (0.8%, 0.38%) in Model 2 (Model 6, Model 10). The activeness of the fund (STDAS) affects fund performance positively, consistent with the findings in Cremers and Petajisto (2009) that funds with a greater active share in their holdings tend to have better performance. However, the relation between STDAS and fund return is not robust. For instance, the benchmark- and FFC-adjusted

Table 5. Active Fund Overpricing and Mutual Fund Performance: Regression Analysis

	Fund performance (in %) regressed on lagged active fund overpricing											
	Return				Benchmark-adjusted return				FFC-adjusted return			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
AFO	−2.528**		−1.484*	−1.639	−2.450**		−1.419*	−1.482	−1.041*		−0.423	−0.385
	(−2.36)		(−1.72)	(−1.67)	(−2.35)		(−1.79)	(−1.63)	(−1.91)		(−0.89)	(−0.67)
COROP		−0.868**				−0.839*				−0.400*		
		(−2.05)				(−2.03)				(−1.79)		
STDAS		0.033**				0.021				0.003		
		(2.37)				(1.42)				(0.29)		
AFO × *Sentiment*			−3.375***	−3.281**			−3.333***	−3.232**			−1.997***	−1.721***
			(−3.14)	(−2.37)			(−3.01)	(−2.29)			(−3.51)	(−2.87)
Active Share				0.656*				0.595*				0.148
				(1.75)				(1.95)				(0.74)
TR^2				−0.027				−0.001				0.003
				(−0.89)				(−0.06)				(0.23)
ICI				0.322				0.379				−0.455
				(0.40)				(0.58)				(−1.24)
Tracking Error				−0.014				−0.003				0.005
				(−0.60)				(−0.12)				(0.27)
lag(*Fund Flow*)	−0.003	−0.003	−0.003	−0.005	−0.002	−0.002	−0.001	−0.002	−0.000	−0.000	−0.000	−0.001
	(−1.51)	(−1.48)	(−1.44)	(−1.14)	(−1.06)	(−1.02)	(−0.99)	(−0.60)	(−0.49)	(−0.47)	(−0.45)	(−0.30)
log(*Fund TNA*)	−0.267***	−0.266***	−0.263***	−0.267***	−0.241***	−0.241***	−0.237***	−0.242***	−0.149***	−0.149***	−0.147***	−0.156***
	(−5.75)	(−5.72)	(−5.64)	(−5.90)	(−6.18)	(−6.17)	(−6.04)	(−6.36)	(−8.88)	(−8.63)	(−8.83)	(−8.75)
Expense Ratio	−0.117**	−0.114**	−0.119**	−0.145**	−0.083	−0.079	−0.084*	−0.103*	−0.022	−0.020	−0.023	−0.051
	(−2.25)	(−2.16)	(−2.32)	(−2.20)	(−1.66)	(−1.56)	(−1.75)	(−1.78)	(−0.65)	(−0.58)	(−0.69)	(−1.39)
Turnover	0.023	0.024	0.022	0.019	0.021	0.021	0.020	0.018	−0.013	−0.012	−0.013	−0.019
	(1.06)	(1.14)	(1.08)	(0.68)	(0.94)	(0.99)	(0.95)	(0.68)	(−0.55)	(−0.53)	(−0.57)	(−0.68)
log(*Fund Age*)	0.040	0.045	0.038	0.043	0.050	0.054	0.048	0.065	0.002	0.003	0.001	0.001
	(0.69)	(0.77)	(0.64)	(0.65)	(1.25)	(1.34)	(1.19)	(1.39)	(0.06)	(0.10)	(0.02)	(0.03)
log(*Manager Tenure*)	−0.004	−0.006	−0.003	0.001	−0.006	−0.007	−0.005	−0.002	−0.000	−0.000	0.001	0.004
	(−0.24)	(−0.35)	(−0.15)	(0.05)	(−0.42)	(−0.50)	(−0.32)	(−0.10)	(−0.03)	(−0.05)	(0.06)	(0.45)
log(*Fund Illiquidity*)	0.121***	0.112**	0.116***	0.104***	0.094**	0.087**	0.089**	0.077**	0.028**	0.027***	0.025**	0.027**
	(2.90)	(2.76)	(2.89)	(2.79)	(2.54)	(2.45)	(2.52)	(2.41)	(2.66)	(2.77)	(2.75)	(2.60)
R^2	0.852	0.852	0.852	0.845	0.072	0.072	0.076	0.079	0.137	0.137	0.140	0.146
Obs.	53,765	53,756	53,765	45,092	53,765	53,756	53,765	45,092	53,765	53,756	53,765	45,092

Notes. This table presents the results of the following quarterly panel regressions with quarter and fund fixed effects and their corresponding t-statistics with standard errors clustered by fund and time:

$$Perf_{f,q} = \alpha_0 + \beta_1 AFO_{f,q-1} + \beta_2 AFO_{f,q-1} \times Sentiment_{q-1} + cM_{f,q-1} + e_{f,q},$$

where $Perf_{f,q}$ is the average monthly performance of fund f in quarter q, $AFO_{f,q-1}$ is the active fund overpricing, $Sentiment_{q-1}$ is the average monthly Baker and Wurgler (2007) market sentiment index, and the vector M stacks all other control variables, including *Active Share*, the (logistic transformation of) *R-square*, *Industry Concentration Index*, *Tracking Error*, lag(*Fund Flow*), log(*Fund TNA*), *Expense Ratio*, *Turnover*, log(*Fund Age*), log(*Manager Tenure*), and log(*Fund Illiquidity*). Note that $AFO_{f,q-1}$ can be further replaced with its two components, $COROP_{f,q-1}$ and $STDAS_{f,q-1}$. The dependent variable $Perf_{f,q}$ is measured by raw return (Models 1–4) and further adjusted by the benchmark return (Models 5–8), as well as the FFC model (Models 9–12). Appendix A provides detailed definitions for each variable.

*, **, and ***Significance at the 10%, 5%, and 1% levels, respectively.

fund returns are not predicted by fund activeness in Models 6 and 10 when we account for the direction of bets with regard to overpricing. Unreported results including all three components (i.e., COROP, STDAS, and STDOP) are qualitatively and quantitatively similar. In particular, mutual fund exposure to dispersion in stock-level overpricing, STDOP, is not significantly related to fund alphas. The latter finding also suggests that the negative effect of AFO on fund performance is not explained by overpriced stocks in the fund's investment universe, emphasizing the uniqueness of the role played by active fund overpricing (i.e., COROP and STDAS) in predicting fund perfo rmance.

To summarize, the panel regression results in Table 5 show that within-fund variation in AFO predicts future fund performance, after controlling for fund characteristics. This relation is driven by the funds being skilled in underweighting (relative to the benchmark portfolio) the overpriced stocks, which is represented by two key components: low correlation between the fund's active weights and stock overpricing (low COROP) and, to a lesser extent, high activeness of the fund (high STDAS). In other words, a highly active fund with high STDAS delivers high future performance if the fund also displays high skill by actively investing in less overpriced stocks (low COROP).

Our previous analyses show that AFO has a stronger effect on fund performance particularly during periods of high sentiment. We reexamine this finding using the panel regression setup in Equation (3) by interacting AFO with investor sentiment:

$$Perf_{f,q} = \alpha_0 + \beta_1 AFO_{f,q-1} + \beta_2 AFO_{f,q-1} \times Sentiment_{q-1} + cM_{f,q-1} + e_{f,q}, \tag{4}$$

where $Sentiment_{q-1}$ is the average monthly Baker and Wurgler (2007) market sentiment index, and all other variables are as defined in Equation (3). To be consistent with the stronger effect of AFO during periods of high sentiment, we expect the slope coefficient capturing the interaction between fund overpricing and investor sentiment (β_2) to be negative. Indeed, we find that the impact of AFO on fund performance is the largest during high sentiment periods. Specifically, in Models 3, 7, and 11 of Table 5, β_2 is negative and significant ranging from −3.375 to −1.997. Hence, active fund overpricing reduces future fund performance and especially so when sentiment is high.

The existing literature has also proposed various proxies for mutual fund managerial skills. As discussed above, Cremers and Petajisto (2009) and Petajisto (2013) show that *Active Share*—the sum of the absolute deviations of the fund's portfolio holdings from its benchmark index holdings—predicts superior fund performance. Additionally, Amihud and Goyenko (2013) employ an alternative active share measure—the *R*-squared obtained from a regression of fund returns on a multifactor benchmark model. They show that a lower *R-squared* (TR^2) is associated with greater selectivity and better performance. Kacperczyk et al. (2005) find that mutual funds with holdings concentrated in only a few industries outperform their more diverse counterparts. Their *Industry Concentration Index* (*ICI*) is defined as the sum of the squared deviations of the fund's portfolio holdings in each industry from the industry weights of the total stock market. Finally, *Tracking Error*—the volatility of the difference between a portfolio return and its benchmark index return—also measures the activeness of fund management (e.g., Cremers and Petajisto 2009).

As a robustness check on the predictive effect of AFO on fund performance, we add these managerial skill proxies as controls in our regression analyses. As reflected in the estimates of Models 4, 8, and 12 in Table 5, we continue to find that AFO significantly predicts lower future fund performance following high sentiment periods, across all three performance specifications. Among the four managerial skill proxies we employ, the fund activeness measured by higher *Active Share* generates the most consistent effect on future fund performance. Overall, our findings so far suggest that mutual funds that actively deviate from their benchmark holdings and take positions in the right (wrong) side of mispricing deliver high (low) future fund performance, emphasizing that AFO is a novel measure of managerial skill.

4.3. AFO and Fund Performance: Robustness Checks

In the first set of robustness checks, we use the regression approach to estimate the cross-sectional relation between AFO and fund returns and report the results in Internet Appendix Table IA2. We estimate the panel regression in Equation (4), with quarter fixed effects only. By removing the fund fixed effects, the panel regression focuses on the cross-fund differences in fund returns. As an alternative, the cross-fund relation between AFO and fund performance is estimated using Fama-MacBeth (1973) regression. As shown in Table IA2, we find a strong, negative relation between AFO and future fund performance across all specifications. Together with the portfolio analyses in the Section 4.1, these findings confirm an economically strong cross-sectional relation between active fund overpricing and mutual fund returns, especially following high sentiment periods.

We also consider the relation between AFO and two other fund performance measures based on the DGTW characteristics model and the dollar-value-added adjustment in the Berk and van Binsbergen (2015) model. Berk and van Binsbergen (2015) employ a measure of skill that is based on the dollar value that a mutual fund adds. They argue that the expected value the fund adds (defined as the product of the benchmark-adjusted fund gross return and lagged asset under management (adjusted by inflation)) is a better measure of skill than the fund's return or alpha. We estimate the same set of panel regressions in Equations (3) and (4), and we find that our results are robust to the DGTW-adjusted return and dollar-value-added-adjusted measures (see Models 1–8 in Table IA3 of the internet appendix). For instance, a one-standard-deviation increase in AFO reduces the fund value by $1.22 million per month, after controlling for other fund characteristics. Overall, our key findings on the negative relation between AFO and fund performance are pervasive.

Next, we examine whether AFO is related to fund performance measure that is unrelated to fund holdings. We do this by employing the return gap measure in Kacperczyk et al. (2008): the difference between the gross-of-fee fund return and the holding-based fund return. As the return gap uses the return of the fund's prior holdings as a benchmark, it adjusts for any performance effects from the fund holdings and captures the impact of interim trading benefits and trading costs in the subsequent quarter. Following Kacperczyk et al. (2008), we construct an abnormal return gap using the FFC model. To reduce the noise in fund returns, we take the average monthly abnormal return gap during three-year intervals (the results are similar if we use a one-year abnormal return gap or raw return gap). As reported in the Internet Appendix Table IA3 (see Models 9–12), we find that AFO and return gap are unrelated. This suggests that the AFO–performance relation is driven by the fund's prior (*active*) holdings of mispriced stocks rather than the fund manager's unobserved actions in the subsequent quarter.

Overall, our active fund overpricing measure predicts lower future fund performance in the cross section and time series, and our findings are robust to various performance measures and model specifications.

4.4. Mispricing Factors

Kogan and Tian (2015) and Stambaugh and Yuan (2017) show that characteristics-based anomalies share common return comovement and factors created from anomalies capture much of the cross-sectional variation in average stock returns. Specifically, Stambaugh and Yuan (2017) propose a four-factor model consisting of the market factor (*RMRF*), the size factor (*SMB*), and two mispricing factors arising from the cluster of anomalies related to firms' managements (*MGMT*) and performance (*PERF*). They show that the four-factor model outperforms alternative models in explaining a large set of anomalies. As Kozak et al. (2018) demonstrate, alphas as a result of mispricing related to investor sentiment are indistinguishable from exposures to mispricing factors. Hence, parsimonious factor models are useful in explaining the cross-sectional variations in expected stock returns due to risk or mispricing. If fund managers actively exploit the return anomalies, do mispricing factors help explain the cross-sectional variation in fund returns? Our purpose here is to explore whether the variation in fund returns that is predicted by the fund's AFO is better explained by the fund's exposure to these mispricing factors.

We start by constructing monthly-rebalanced decile portfolios according to lagged AFO as in Table 4. Holding-period portfolio returns are adjusted by the Stambaugh and Yuan (2017) four-factor model. Panel A of Table 6 presents the portfolio alphas and factor loadings in the four-factor model for each of the decile portfolios as well as the differential return between the least and the most overpriced fund deciles ("LMH"). We find that the mispricing factors play an important role in capturing the cross-sectional fund returns based on AFO. The factor loading on *MGMT* (*PERF*) is statistically significant in 8 (4) out of 10 portfolio returns sorted on AFO. In addition, high AFO funds display significant negative exposure to both mispricing factors, whereas the low AFO funds show significant positive exposure to *MGMT* factor. As a result, the investment strategy that takes a long position in low AFO funds and short position in high AFO funds exhibits significant positive factor loadings on both mispricing factors and has significant negative loadings on the *SMB* factor. Interestingly, the predictive effect of AFO on unconditional fund returns is adequately captured by the Stambaugh and Yuan (2017) factors, resulting in an insignificant average alpha for the LMH portfolio.

In panel B of Table 6, we report the results from quarterly panel regressions as in Equations (3) and (4), where the dependent variable is the average monthly Stambaugh and Yuan (2017) four-factor-adjusted return in each quarter. We include quarter and fund fixed effects to capture within fund variations in AFO–performance relation. Unreported results are qualitatively and quantitatively similar when we only include the quarter fixed effects and apply Fama-MacBeth (1973) regressions. In line with the portfolio results in panel A, the levels of AFO and COROP do not predict mispricing factor-adjusted fund returns. This is consistent with the notion that the return predictability of AFO is related to the fund's holdings of mispriced stocks. Because fund managers actively bet on mispriced stocks, it is also not surprising that the four-factor model proposed by Stambaugh and Yuan (2017) provides an adequate approach to evaluate the unconditional performance of mutual fund managers. However, the predictability

Table 6. Mutual Fund Returns Adjusted by Mispricing Factors

Panel A. Mispricing factor-adjusted returns to investment strategies sorted by active fund overpricing

	Low	2	3	4	5	6	7	8	9	High	LMH
Intercept	−0.045	−0.076*	−0.090**	−0.088*	−0.088*	−0.102**	−0.078	−0.034	−0.002	0.033	−0.078
	(−0.66)	(−1.65)	(−2.22)	(−1.93)	(−1.77)	(−2.28)	(−1.45)	(−0.60)	(−0.02)	(0.50)	(−0.92)
RMRF	0.895***	0.941***	0.954***	0.937***	0.937***	0.995***	0.960***	0.958***	0.932***	0.941***	−0.047
	(40.73)	(59.51)	(68.34)	(61.67)	(61.83)	(60.64)	(61.78)	(61.56)	(32.64)	(46.03)	(−1.53)
SMB	0.108***	−0.010	−0.027	−0.030	−0.045*	0.019	0.033	0.058	0.079***	0.185***	−0.077**
	(3.07)	(−0.29)	(−1.18)	(−1.42)	(−1.66)	(0.61)	(1.09)	(1.61)	(2.70)	(5.50)	(−1.98)
MGMT	0.137***	0.092***	0.101***	0.105***	0.053**	0.077***	0.017	−0.010	−0.083**	−0.188***	0.325***
	(4.30)	(4.18)	(4.59)	(4.03)	(2.39)	(3.07)	(0.62)	(−0.40)	(−2.55)	(−7.71)	(8.25)
PERF	0.024	0.032*	0.028*	0.022	0.023	0.036**	0.013	−0.007	−0.027	−0.094***	0.117***
	(1.13)	(1.95)	(1.83)	(1.33)	(1.24)	(2.14)	(0.75)	(−0.49)	(−1.38)	(−5.03)	(3.59)
Obs.	348	348	348	348	348	348	348	348	348	348	348

Panel B. Mispricing factor-adjusted fund performance (in %) regressed on lagged active fund overpricing

	Model 1	Model 2	Model 3	Model 4
AFO	−0.535		−0.003	0.104
	(−0.95)		(−0.01)	(0.18)
COROP		−0.188		
		(−0.82)		
STDAS		0.008		
		(0.50)		
AFO × Sentiment			−1.717***	−1.440*
			(−2.95)	(−1.93)
Active Share				−0.012
				(−0.04)
TR^2				0.019
				(1.12)
ICI				0.138
				(0.25)
Tracking Error				0.008
				(0.36)
lag(*Fund Flow*)	−0.002	−0.002	−0.002	−0.003
	(−1.43)	(−1.44)	(−1.39)	(−1.12)
log(*Fund TNA*)	−0.148***	−0.147***	−0.146***	−0.155***
	(−9.58)	(−9.55)	(−9.37)	(−9.76)
Expense Ratio	−0.084*	−0.083*	−0.084*	−0.130**
	(−1.79)	(−1.75)	(−1.84)	(−2.46)
Turnover	−0.031	−0.031	−0.031	−0.031
	(−0.92)	(−0.91)	(−0.93)	(−0.83)
log(*Fund Age*)	0.001	0.003	0.000	0.001
	(0.04)	(0.08)	(0.01)	(0.02)
log(*Manager Tenure*)	0.006	0.006	0.007	0.011
	(0.50)	(0.46)	(0.56)	(0.98)
log(*Fund Illiquidity*)	0.017	0.015	0.014	0.020
	(1.12)	(1.08)	(0.96)	(1.53)
R^2	0.149	0.149	0.151	0.158
Observations	53,765	53,756	53,765	45,092

Notes. In panel A, mutual funds are sorted into deciles according to lagged AFO in month m. We report the month $m+1$ (value-weighted) performance for each decile portfolio as well as the strategy of going long (short) the one-month underpriced (overpriced) funds ("LMH") over the entire sample period from 1981 to 2010. Fund returns are adjusted by the Stambaugh and Yuan (2017) model, including the market factor (*RMRF*), the size factor (*SMB*), and two mispricing factors arising from cluster of anomalies related to firms' managements (*MGMT*) and performance (*PERF*). Models 1–4 in panel B present the results of the following quarterly panel regressions with quarter and fund fixed effects and their corresponding t-statistics with standard errors clustered by fund and time:

$$Perf_{f,q} = \alpha_0 + \beta_1 AFO_{f,q-1} + \beta_2 AFO_{f,q-1} \times Sentiment_{q-1} + cM_{f,q-1} + e_{f,q},$$

where $Perf_{f,q}$ is the average monthly Stambaugh and Yuan (2017) four-factor-adjusted return of fund f in quarter q, $AFO_{f,q-1}$ is the active fund overpricing, $Sentiment_{q-1}$ is the average monthly Baker and Wurgler (2007) market sentiment index, and the vector M stacks all other control variables, including *Active Share*, the (logistic transformation of) *R-square*, *Industry Concentration Index*, *Tracking Error*, lag(*Fund Flow*), log(*Fund TNA*), *Expense Ratio*, *Turnover*, log(*Fund Age*), log(*Manager Tenure*), and log(*Fund Illiquidity*). Note that $AFO_{f,q-1}$ can be further replaced with its two components, $COROP_{f,q-1}$ and $STDAS_{f,q-1}$. Appendix A provides detailed definitions for each variable.

*, **, and ***Significance at the 10%, 5%, and 1% levels, respectively.

of AFO on mispricing factor-adjusted fund performance emerges during periods of high investor sentiment (see Models 3 and 4 of Table 6). The latter is consistent with AFO also reflecting the manager's (time-varying) preference for overpriced stocks, which is not fully explained by the mispricing factors. Nevertheless, the superior ability of the Stambaugh and Yuan (2017) mispricing factor model in explaining the AFO effect on funds suggests that mispricing-based models of expected fund returns might be an interesting avenue to explain delegated portfolio returns in future work.

5. Active Fund Overpricing and Fund Flows

Our findings suggest that mutual funds vary in their propensity to actively expose to overpriced stocks, leading to an economically significant impact on the payoff received by their investors. In this section, we investigate how mutual fund investors react to active fund overpricing, as measured by subsequent net fund flows. Interestingly, the assertion in Miller (1977) is consistent with actively overpriced funds being most likely held by optimistic investors. Specifically, in periods of high sentiment, overpriced funds could attract additional flows as optimistic investors, buoyed by positive market sentiment, pour more money into these funds. Alternatively, mutual fund investors are known to chase past performance (e.g., Chevalier and Ellison 1997), and overpriced funds are typically recent underperformers. Hence, we examine the empirical relation between fund overpricing and future flows, after controlling for the effects of past fund performance.

To assess the relation between active fund overpricing and fund flows, we estimate the quarterly panel regressions of the following form:

$$Flow_{f,q} = \alpha_0 + \beta_1 AFO_{f,q-1} + \beta_2 AFO_{f,q-1} \times Sentiment_{q-1} + \beta_3 Perf_{f,q-1} + cM_{f,q-1} + e_{f,q}, \tag{5}$$

where $Flow_{f,q}$ refers to the average monthly flow or benchmark-adjusted flow of fund f in quarter q, $Perf_{f,q-1}$ refers to the average monthly return of fund f in quarter $q-1$, and all other variables are defined as in Equations (3) and (4). We include quarter and fund fixed effects, with standard errors clustered at both fund and time levels.

Table 7 presents the results, with Models 1–4 on fund flows and Models 5–8 on benchmark-adjusted flows. As expected, past performance is a strong predictor of flows as slope coefficients of past fund return variables are positive and economically large. Consistent with the well-documented flow–performance relation, a one-standard-deviation increase in past quarter fund return increases fund flows by 10.67% (Model 1). The effect of past fund returns applies to fund returns measured over the past one quarter and the previous three quarters. Additionally, fund flows are also higher when fund manager tenure is higher and older funds are associated with lower flows. Focusing on the predictive power of AFO, which is the core of our analysis, several findings are noteworthy. First, there is a positive relationship between AFO and fund flow, and this result is unaffected by controlling for various fund characteristics (including past fund returns). A one-standard-deviation increase in AFO is associated with a higher annual flow of 0.74% (Model 1), although the economic magnitude is considerably smaller than the effect of past returns. Second, the AFO–fund flow relation is sensitive to the state of market sentiment. In particular, the positive AFO–flow relationship is amplified when investor sentiment is high, as the interaction between overpricing and sentiment is positive and highly significant in Model 2. Moreover, the level of AFO no longer predicts fund flow with the inclusion of the interaction term, suggesting that high AFO funds attract additional flows only during periods of high sentiment. Finally, when we interact past fund returns with the sentiment indicator in Model 3, we find that the positive effect of past returns on flows is weakened during high sentiment periods. This is in contrast to the strengthening of overpricing effect on flows in high sentiment periods. The empirical evidence implies that mutual fund investors are less sensitive to past fund performance during high sentiment periods, which generates the positive relation between AFO and future flows. This is not surprising because fund-level overpricing is not directly observable by investors. This finding is also unaffected by the control for other managerial skill measures. In unreported results, we also obtain a similar positive cross-sectional relation between AFO and subsequent fund flows as reflected in the panel regression with only quarter fixed effects and Fama-MacBeth (1973) regression.

The positive relation between active fund overpricing and future flows is robust to alternative specifications. Because fund flows could be driven by investor demand in a particular style or benchmark, Models 5–8 of Table 7 investigate the benchmark-adjusted flow, where the fund flows are adjusted by netting out their benchmark average flows. The tests based on benchmark-adjusted flow provide-confirming evidence that overpriced funds attract more investor capitals, especially during periods of high sentiment when flows are less sensitive to past performance. Moreover, our findings are not simply driven by mutual fund investors chasing a particular style. In unreported results, we also confirm that the findings are qualitatively similar when we focus on the first component of AFO (i.e., COROP), which proxies for

Table 7. Active Fund Overpricing and Flows

	Fund flow (in %) regressed on lagged active fund overpricing							
	Flow				Benchmark-adjusted fund flow			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
AFO	1.770*	1.045	1.572*	1.206	1.980**	1.319	1.805*	1.445*
	(1.99)	(1.15)	(1.81)	(1.58)	(2.17)	(1.45)	(2.03)	(1.85)
AFO × *Sentiment*		2.688**		0.969		2.453**		0.737
		(2.50)		(0.91)		(2.30)		(0.72)
Fund Return$_{q\text{-}1}$ × *Sentiment*			−0.157***	−0.141***			−0.139***	−0.125***
			(−6.41)	(−7.62)			(−7.30)	(−8.20)
Active Share				0.510				0.534
				(1.26)				(1.36)
TR^2				0.057**				0.072***
				(2.69)				(2.99)
ICI				−1.072				−0.733
				(−1.03)				(−0.73)
Tracking Error				−0.031				−0.035*
				(−1.40)				(−1.71)
lag(*Fund Flow*)	0.126	0.125	0.124	0.317***	0.127	0.127	0.126	0.324***
	(1.58)	(1.58)	(1.58)	(13.30)	(1.57)	(1.57)	(1.57)	(13.08)
Fund Return$_{q\text{-}1}$	0.275***	0.278***	0.356***	0.322***	0.249***	0.252***	0.321***	0.293***
	(4.26)	(4.36)	(7.81)	(8.91)	(4.70)	(4.80)	(8.12)	(9.11)
Fund Return$_{q\text{-}4:q\text{-}2}$	0.565***	0.573***	0.596***	0.438***	0.550***	0.557***	0.577***	0.424***
	(4.26)	(4.36)	(4.84)	(4.93)	(4.41)	(4.50)	(4.91)	(4.90)
log(*Fund TNA*)	−0.598***	−0.601***	−0.615***	−0.670***	−0.600***	−0.603***	−0.615***	−0.665***
	(−8.26)	(−8.28)	(−8.73)	(−9.00)	(−8.55)	(−8.56)	(-8.97)	(−9.06)
Expense Ratio	0.093	0.093	0.115	−0.184	0.084	0.084	0.104	−0.192
	(0.45)	(0.45)	(0.55)	(−1.17)	(0.40)	(0.40)	(0.49)	(−1.21)
Turnover	−0.021	−0.021	−0.022	−0.060	−0.039	−0.038	−0.039	−0.070
	(-0.35)	(−0.34)	(−0.36)	(−1.09)	(−0.60)	(−0.59)	(−0.61)	(−1.24)
log(*Fund Age*)	−1.212***	−1.212***	−1.205***	−0.820***	−1.100***	−1.100***	−1.094***	−0.724***
	(−5.49)	(−5.49)	(−5.55)	(−5.20)	(−5.20)	(−5.20)	(−5.25)	(−4.55)
log(*Manager Tenure*)	0.115***	0.114***	0.119***	0.097**	0.122***	0.121***	0.126***	0.102***
	(2.94)	(2.92)	(3.14)	(2.68)	(3.23)	(3.21)	(3.40)	(2.89)
R^2	0.276	0.276	0.280	0.344	0.266	0.266	0.269	0.335
Observations	55,901	55,901	55,901	45,092	55,901	55,901	55,901	45,092

Notes. This table presents the results of the following quarterly panel regressions with quarter and fund fixed effects and their corresponding *t*-statistics with standard errors clustered by fund and time:

$$Flow_{f,q} = \alpha_0 + \beta_1 AFO_{f,q-1} + \beta_2 AFO_{f,q-1} \times Sentiment_{q-1} + \beta_3 Perf_{f,q-1} + cM_{f,q-1} + e_{f,q},$$

where $Flow_{f,q}$ refers to the average monthly flow (Models 1–4) and benchmark-adjusted flow (Models 5–8) of fund f in quarter q, $AFO_{f,q-1}$ is the active fund overpricing, $Sentiment_{q-1}$ is the average monthly Baker and Wurgler (2007) market sentiment index, $Perf_{f,q-1}$ is the average monthly fund return, and the vector M stacks all other control variables, including *Active Share*, the (logistic transformation of) *R-square*, *Industry Concentration Index*, *Tracking Error*, lag(*Fund Flow*), log(*Fund TNA*), *Expense Ratio*, *Turnover*, log(*Fund Age*), and log(*Manager Tenure*). Appendix A provides detailed definitions for each variable.

*, **, and ***Significance at the 10%, 5%, and 1% levels, respectively.

the stock picking skill. Hence, high AFO funds attract additional flows during high sentiment periods despite their poor recent performance, because optimistic investors are less sensitive to past performance.

The overall evidence suggests that although managers of high AFO funds exhibit low stock picking skills, they seem to be rewarded with positive flows during high sentiment periods, consistent with investor optimism reducing flow-performance sensitivity and perpetuating active fund overpricing. Our findings imply that skilled managers compete on performance and attract capital through their attempts to outperform benchmarks (i.e., betting on the right direction of mispricing), whereas less skilled or sentiment-driven managers attract investor flows as a result of investor optimism, particularly during high sentiment periods. We also note that more overpriced funds charge high (fixed) fees (see Table 2); therefore low-skilled managers are better off by remaining active instead of adopting a passive, low-fee strategy. The latter findings are also consistent with the mutual fund sector trading on the wrong side of the mispricing (Edelen et al. 2016).

6. Conclusion

In this paper, we propose a new measure of fund investment skill, AFO, measuring the fund's holding of mispriced stocks relative to their benchmark portfolio. More precisely, AFO captures the covariance between the fund's active portfolio weights (i.e., the fund's active deviation of stock holdings from the benchmark implied investment weights) and overpricing of the stocks in the fund's investment universe. We identify the stock-level overpricing by averaging the overpricing implied by 11 prominent stock market anomalies in Stambaugh et al. (2012). AFO predicts future fund returns under the premise that skilled (unskilled) fund managers *actively* underweight (overweight) overpriced stocks and realize superior (inferior) performance as the stock overpricing subsides in the future.

We find strong evidence of low AFO funds outperforming high AFO funds in the subsequent quarter. In particular, funds that rank in the top decile in terms of AFO underperform funds in the bottom AFO decile by 2.27% (2.1%) per year in benchmark-adjusted (style-adjusted) returns. Adjusting for risk exposures based on commonly employed factor models, the difference in low and high AFO decile alphas ranges from 1.8% (FFC four-factor model) to 3.56% (CAPM) per annum. We obtain qualitatively similar predictable cross-sectional variation in fund returns related to AFO after accounting for differences in the fund characteristics as well as other known measures of fund manager skill. We also document significant time-series variation in the fund-level AFO–performance relation. Moreover, the negative AFO–performance relation is enhanced when investor sentiment is high, consistent with AFO being more impactful when investors are optimistic.

Additional evidence based on the decomposition of AFO sheds light on the mechanism that links AFO and subsequent fund returns. AFO is the product of three elements: (i) the fund's active stock picking skill reflected in the correlation between active fund holdings and stock overpricing (COROP), (ii) the degree of activeness of the fund (equivalent to its active share) (STDAS), and (iii) the fund's investment opportunity in terms of mispriced stocks (STDOP). We find that the first component, COROP, is the strongest and most consistent predictor of fund returns. The weak evidence on the predictability of fund returns based on STDAS reveals the inadequacy of fund activeness as a measure of investment skill as high activeness does not account for the quality of the fund's investment bets (Cremers and Petajisto 2009, Frazzini et al. 2016). Our results highlight the notion that a high active share fund (high STDAS) may be expected to earn high or low future returns depending on whether the fund is actively under- or overweighting overpriced stocks. Hence, AFO provides an improvement to the active share measure by incorporating the ex ante stock picking ability of the fund.

Whereas recent evidence show that mutual funds as a whole are on the wrong side of anomalies (e.g., Akbas et al. 2015, Edelen et al. 2016), we find that there are significant cross-sectional variations in mutual funds' active exposure to stock mispricing, which in turn predicts fund future performance. Collectively, our evidence is consistent with the persistent exposure of active mutual funds to overpriced stocks revealing an aspect of stock selection skills. Moreover, as our proposed active fund overpricing measure combines the active management with manager's ability to identify mispriced stocks, it generates additional power to identify skilled managers.

Acknowledgments

The authors thank two anonymous referees, the associate editor, Yakov Amihud, Scott Cederburg, Alexander Chinco, Martin Cremers, Karl Diether (editor), Joni Kokkonen, Lin Peng, Jianfeng Shen, Ashley Wang, and Hong Zhang; and seminar participants at INSEAD, Queen's University Belfast, Shanghai Advanced Institute of Finance (SAIF), Tel Aviv University, the Chinese University of Hong Kong, Tsinghua University, University College Dublin, the University of New South Wales, the University of Sydney, the University of Technology Sydney, the 2015 Luxembourg Asset Management Summit, the 2015 Tel Aviv Finance Conference, the 2016 China International Conference on Finance, and the 2016 FMA European Conference for helpful comments.

Appendix A. Variable Definitions

Variable	Definition
A. Anomaly measures	
Failure Probability	Failure probability in a given month t is computed as follows: $Distress_{i,t} = -9.164 - 20.264 \times \overline{NIMTA}_{i,t} + 1.416 \times TLMTA_{i,t} - 7.129 \times \overline{EXRET}_{i,t} + 1.411 \times SIGMA_{i,t} - 0.045 \times RSIZE_{i,t} - 2.132 \times CASHMTA_{i,t} + 0.075 \times MB_{i,t} - 0.058 \times PRICE_{i,t}$, where $TLMTA_{i,t}$ is the ratio of total liabilities (COMPUSTAT quarterly item LTQ) divided by the sum of market equity and total liabilities of stock i in month t, $SIGMA_{i,t}$ is the annualized three-month rolling sample standard deviation, $RSIZE_{i,t}$ is the logarithm of the ratio of the stock market equity to that of the S&P 500 index, $CASHMTA_{i,t}$ is the ratio of cash and short-term investments (item CHEQ) divided by the sum of market equity and total liabilities, $MB_{i,t}$ is the market-to-book ratio, and $PRICE_{i,t}$ is the logarithm of the price per share and truncated above at USD15. We furthermore compute $\overline{NIMTA}_{i,t}$ and $\overline{EXRET}_{i,t}$ as follows: $\overline{NIMTA}_{i,t} = \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{i,t-3:t-1} + \cdots + \phi^9 NIMTA_{i,t-12:t-10})$, $\overline{EXRET}_{i,t} = \frac{1-\phi}{1-\phi^{12}}(EXRET_{i,t-1} + \cdots + \phi^{11} EXRET_{i,t-12})$, and $EXRET_{i,t} = \log(1 + R_{i,t}) - \log(1 + R_{S\&P500,t})$, where $\phi = 2^{-1/3}$, $NIMTA_{i,t-3:t-1}$ is the ratio of net income (item NIQ) divided by the sum of market equity and total liabilities, $R_{i,t}$ is the return of stock i in month t, and $R_{S\&P500,t}$ is the return of S&P 500 index, following Campbell et al. (2008) and Chen et al. (2011).
O-Score	O-score in a given quarter q is computed as follows: $OScore_{i,q} = -1.32 - 0.407 \times \log(ADJASSET_{i,q}/CPI_q) + 6.03 \times TLTA_{i,q} - 1.43 \times WCTA_{i,q} + 0.076 \times CLCA_{i,q} - 1.72 \times OENEG_{i,q} - 2.37 \times NITA_{i,q} - 1.83 \times FUTL_{i,q} + 0.285 \times INTWO_{i,q} - 0.521 \times CHIN_{i,q}$, where $ADJASSET_{i,q}$ is the adjusted total assets of stock i in quarter q, defined as total assets (COMPUSTAT quarterly item ATQ) plus 10% of the difference between market equity and book equity; CPI_q is the consumer price index; $TLTA_{i,q}$ is the leverage ratio defined as the book value of debt (item DLCQ plus item DLTTQ) divided by $ADJASSET_{i,q}$; $WCTA_{i,q}$ is the ratio of working capital (item ACTQ – item LCTQ) divided by $ADJASSET_{i,q}$, $CLCA_{i,q}$ is the ratio of current liabilities (item LCTQ) divided by current assets (item ACTQ), $OENEG_{i,q}$ is a dummy variable taking a value of 1 if total liabilities (item LTQ) exceeds total assets and 0 otherwise, $NITA_{i,q}$ is the ratio of net income (item NIQ) divided by $ADJASSET_{i,q}$; $FUTL_{i,q}$ is the ratio of fund provided by operations (item PIQ) divided by total liabilities; and $INTWO_{i,q}$ is a dummy variable taking a value of 1 if the net income is negative for the last two quarters and 0 otherwise. We furthermore compute $CHIN_{i,q}$ as follows: $CHIN_{i,q} = (NI_{i,q} - NI_{i,q-1})/(\lvert NI_{i,q}\rvert + \lvert NI_{i,q-1}\rvert)$, where $NI_{i,q}$ is the net income of stock i in quarter q, following Ohlson (1980) and Chen et al. (2011).
Net Stock Issuance	Net stock issuance in a given year t is computed as follows: $NetStk_{i,t} = \log(SHROUT_{i,t}/SHROUT_{i,t-1})$, where $SHROUT_{i,t}$ is the split-adjusted number of shares outstanding of stock i in year t.
Composite Equity Issuance	Composite equity issuance in a given year t is computed as follows: $CompEqu_{i,t} = \log(ME_{i,t}/ME_{i,t-5}) - LR_{i,t-5:t}$, where $ME_{i,t}$ is the market equity of stock i in year t, and $LR_{i,t-5:t}$ is the cumulative log return on stock i over the previous five years, following Daniel and Titman (2006).
Total Accruals	Total accruals in a given year t is computed as follows: $Accruals_{i,t} = [(\Delta CA_{i,t} - \Delta Cash_{i,t}) - (\Delta CL_{i,t} - \Delta STD_{i,t} - \Delta TP_{i,t}) - Dep_{i,t}]/\overline{ASSET}_{i,t}$, where $\Delta CA_{i,t}$ is the change in current assets (COMPUSTAT annual item ACT) of stock i in year t, $\Delta Cash_{i,t}$ is the change in cash and short-term investments (item CHE), $\Delta CL_{i,t}$ is the change in current liabilities (item LCT), $\Delta STD_{i,t}$ is the change in debt included in current liabilities (item DLC), $\Delta TP_{i,t}$ is the change in income taxes payable (item TXP), $Dep_{i,t}$ is the depreciation and amortization expense (item DP), and $\overline{ASSET}_{i,t}$ is the average total assets (item AT) of the beginning and end of year t, following Sloan (1996).
Net Operating Assets	Net operating assets in a given year t is computed as follows: $NOA_{i,t} = [(ASSET_{i,t} - Cash_{i,t}) - (ASSET_{i,t} - STD_{i,t} - LTD_{i,t} - MI_{i,t} - PS_{i,t} - CE_{i,t})]/ASSET_{i,t-1}$, where $ASSET_{i,t}$ is the total assets (COMPUSTAT annual item AT) of stock i in year t, $Cash_{i,t}$ is the cash and short-term investments (item CHE), $STD_{i,t}$ is the debt included in current liabilities (item DLC), $LTD_{i,t}$ is the long-term debt (item DLTT), $MI_{i,t}$ is the minority interests (item MIB), $PS_{i,t}$ is the preferred stocks (item PSTK), and $CE_{i,t}$ is the common equity (item CEQ), following Hirshleifer et al. (2004).
Momentum	Formation period return in a given month m is computed as the cumulative six-month return from month $m - 6$ to month $m - 1$, following Jegadeesh and Titman (1993).

Appendix A. (Continued)

Variable	Definition
Gross Profitability	Gross profitability in a given year t is computed as follows: $GP_{i,t} = (REVT_{i,t} - COGS_{i,t})/ASSET_{i,t}$, where $REVT_{i,t}$ is the total revenue (COMPUSTAT annual item REVT) of stock i in year t, $COGS_{i,t}$ is the cost of goods sold (item COGS), and $ASSET_{i,t}$ is the total assets (item AT), following Novy-Marx (2013).
Asset Growth	Asset growth in a given year t is computed as follows: $ASSETG_{i,t} = (ASSET_{i,t} - ASSET_{i,t-1})/ASSET_{i,t-1}$, where $ASSET_{i,t}$ is the total assets (COMPUSTAT annual item AT) of stock i in year t, following Cooper et al. (2008).
Return on Assets	Return on assets in a given quarter q is computed as follows: $ROA_{i,q} = INCOME_{i,q}/ASSET_{i,q-1}$, where $INCOME_{i,q}$ is the income before extraordinary items (COMPUSTAT quarterly item IBQ) of stock i in quarter q, and $ASSET_{i,q-1}$ is the total assets (item ATQ).
Abnormal Capital Investment	Abnormal capital investment in a given year t is computed as follows: $CI_{i,t} = \frac{CE_{i,t}}{(CE_{i,t-1}+CE_{i,t-2}+CE_{i,t-3})/3} - 1$, where $CE_{i,t}$ is the ratio of capital expenditures (COMPUSTAT annual item CAPX) divided by sales (item SALE) of stock i in year t, following Titman et al. (2004).
Overpricing	For each of the 11 anomalies above, we rank the stocks in each quarter with the highest rank indicating the most overpriced stock (lowest future return), and the ranks are normalized to follow a [0, 1] uniform distribution. A stock's composite rank is the equal-weighted average of its ranks for all anomalies, following Stambaugh et al. (2015).
B. Managerial skill measures	
AFO	Active fund overpricing in a given quarter q is computed as follows: $AFO_{f,q} = \sum_i (w_{i,f,q} - w^b_{i,f,q})O_{i,q}$, where $w_{i,f,q}$ is the investment weight of stock i by fund f in quarter q, $w^b_{i,f,q}$ is the investment weight of stock i in fund f's benchmark portfolio in the same quarter, $O_{i,q}$ is the mispricing measure (*Overpricing* as defined above) for stock i in the same quarter. This measure can be further decomposed to three components, $AFO_{f,q} = \rho(w_{i,f,q} - w^b_{i,f,q}, O_{i,q})N_{f,q}\sigma(w_{i,f,q} - w^b_{i,f,q})\sigma(O_{i,q}) = COROP_{f,q} \times STDAS_{f,q} \times STDOP_{f,q}$.
COROP	The active stock picking skill in a given quarter q is computed as follows: $COROP_{f,q} = \rho(w_{i,f,q} - w^b_{i,f,q}, O_{i,q})$, where all variables are defined as in *AFO*.
STDAS	The degree of activeness in a given quarter q is computed as follows: $STDAS_{f,q} = N_{f,q}\sigma(w_{i,f,q} - w^b_{i,f,q})$, where $N_{f,q}$ is the number of stocks in fund f's investment universe, including those held by the fund and those in the fund's benchmark index. All other variables are defined as in *AFO*.
STDOP	The standard deviation of overpricing in a given quarter q is computed as follows: $STDOP_{f,q} = \sigma(O_{i,q})$, where all variables are defined as in *AFO*.
Active Share	Active share in a given quarter q is computed as follows: $AS_{f,q} = \frac{1}{2}\sum_i \lvert w_{i,f,q} - w^b_{i,f,q}\rvert$, following Cremers and Petajisto (2009) and Petajisto (2013). All variables are defined as in *AFO*.
TR^2	The R-square of fund f in a given month m, $R^2_{f,m}$ is obtained from the FFC four-factor model with a 24-month estimation period. More specifically, we regress monthly fund excess return on the market, size, book-to-market, and momentum factor returns. The logistic transformation of R-square in a given month m is then computed as follows: $TR^2_{f,m} = \log[\sqrt{R^2_{f,m} + c}/(1 - \sqrt{R^2_{f,m} + c})]$, where $c = 0.5/n$, and n is the sample size ($n = 24$), following Amihud and Goyenko (2013).
ICI	Industry concentration index in a given quarter q is computed as follows: $ICI_{f,q} = \sum_{j=1}^{10} (\omega_{j,f,q} - \bar{\omega}_{j,q})^2$, where $\omega_{j,f,q}$ is the investment weight of industry j in fund f in quarter q, and $\bar{\omega}_{j,q}$ is the investment weight of industry j in the market portfolio in the same quarter, following Kacperczyk et al. (2005).
Tracking Error (in %)	Tracking error in a given quarter q is computed as the standard deviation of the difference between the monthly fund gross-of-fee return and its gross-of-fee benchmark index return.
C. Fund performance and flow measures (in %)	
Fund Return	The monthly return reported by the CRSP survivorship bias-free mutual fund database. When a portfolio has multiple share classes, its total return is computed as the share class TNA-weighted return of all share classes, where the TNA values are one-month lagged.
Benchmark-adjusted Return	Fund returns minus the average return of the funds in the same benchmark, defined as the Lipper objective in the CRSP mutual fund database.
Style-adjusted Return	Fund returns minus the average return of the funds in the same style, defined as the 3×3 Morningstar style box.

Appendix A. (Continued)

Variable	Definition
FFC-adjusted Return	Fund returns minus the productions between a fund's four-factor betas multiplied by the realized four-factor returns in a given month. The four FFC factors include market, size, book-to-market, and momentum. The betas of the fund are estimated as the exposures of the fund to the relevant risk factors with a five-year estimation period.
DGTW-adjusted Return	The investment value-weighted average of stock-level DGTW-adjusted returns, according to a fund's most recently reported holding information. More specifically, stock returns are adjusted by the style average, where stock styles are created by double-sorting stocks into 25 independent book-to-market and size portfolios, following Daniel et al. (1997).
Fund Flow	Fund flow in a given month m is computed as follows: $Flow_{f,m} = [TNA_{f,m} - TNA_{f,m-1} \times (1 + r_{f,m})]/TNA_{f,m-1}$, where $TNA_{f,m}$ refers to the total net asset of fund f in month m, and $r_{f,m}$ refers to fund total return in the same month.
D. Stock characteristics	
log(*Stock Illiquidity*)	The logarithm of the stock illiquidity, and the stock illiquidity measure in a given month m is computed as follows: $ILLIQ_{i,m} = (\sum_{d\in m} \lvert R_{i,d,m}\rvert / VOLD_{i,d,m})/D_{i,m} \times 10^8$, where $R_{i,d,m}$ refers to the percentage return of stock i in day d of month m, $VOLD_{i,d,m}$ refers to the dollar trading volume at the same time, and $D_{i,m}$ is the number of trading days for stock i in month m, following Amihud (2002).
Mutual Fund Ownership (in %)	The mutual fund ownership in a given quarter q is computed as follows: $IO_{i,q} = \sum_f SHR_{i,f,q}/SHROUT_{i,q}$, where $SHR_{i,f,q}$ refers to the number of shares of stock i held by fund f in quarter q, and $SHROUT_{i,q}$ refers to the shares outstanding at the same time.
Analyst Coverage	The number of analyst following the firm as reported in I/B/E/S in each quarter.
Stock IdioVol (in %)	For each stock i, a Fama and French three-factor model is estimated using daily returns in each month m: $R^e_{i,d,m} = \alpha_i + \beta_{MKT,i} MKT_{d,m} + \beta_{SMB,i} SMB_{d,m} + \beta_{HML,i} HML_{d,m} + e_{i,d,m}$, where $R^e_{i,d,m}$ refers to the excess return of stock i in day d of month m; and $MKT_{d,m}$, $SMB_{d,m}$, and $HML_{d,m}$ refer to the three Fama and French factors (market, size, and book-to-market). The idiosyncratic volatility for stock i in month m is computed as the standard deviation of the residual $e_{i,d,m}$, following Ang et al. (2006).
E. Other fund characteristics	
log(*Fund TNA*)	The logarithm of total net asset as reported in the CRSP survivorship bias-free mutual fund database, in millions.
Expense Ratio (in %)	The annualized expense ratio as reported in the CRSP survivorship bias-free mutual fund database.
Turnover	The annualized turnover ratio as reported in the CRSP survivorship bias-free mutual fund database.
log(*Fund Age*)	The logarithm of number of operational months since inception.
log(*Manager Tenure*)	The logarithm of number of months since the current portfolio manager took control.
log(*Fund Illiquidity*)	The logarithm of the investment value-weighted average of illiquidity of stocks in a fund's most recently reported holding portfolio. The Amihud stock illiquidity measure is computed as in log(*Stock Illiquidity*) above.

Endnotes

[1] There is some, albeit limited, evidence that mutual funds profit from anomalies. For example, the top 10% of mutual funds that actively follow the accrual strategy earn positive alphas (Ali et al. 2008). Furthermore, others show that anomalies such as momentum survive reasonable transaction costs incurred by institutions (Korajczyk and Sadka 2004).

[2] Our evidence on the cross-sectional relation between fund overpricing and performance adds to the findings of Pástor et al. (2017) on the relation between time variation in fund trading activity and manager skill. They find that funds trade more when investor sentiment is high, consistent with funds trading heavily when stocks are more mispriced.

[3] As most anomalies are formed annually and do not vary within a quarter, we also construct the overpricing measure at the annual frequency. Our findings are similar across these sampling frequencies.

[4] Frazzini et al. (2016), for example, assert that "active share is a measure of active risk, and simply taking on more risk is unlikely, by itself, to lead to outperformance" (p. 15).

[5] We thank Antti Petajisto for making the active share data publicly available: http://www.petajisto.net/data.html (accessed March 31, 2019).

[6] In Table 4, the monthly return difference between the least and the most active overpriced funds is 0.194%, which translates to an annualized return of 0.194% × 12 = 2.33%.

[7] Notice that the average risk and style-adjusted (net-of-fee) return of mutual funds is generally found to be negative (e.g., Malkiel 1995, Gruber 1996, Carhart 1997, Wermers 2000, Christoffersen and Musto 2002, Gil-Bazo and Ruiz-Verdú 2009). Similarly, in our entire sample of mutual funds, unreported results show that the annualized CAPM-adjusted alpha is −0.22% (t = −0.62) and the FFC-adjusted alpha is −0.48% (t = −1.38).

[8] We thank Jeffry Wurgler for making their index of investor sentiment publicly available. Following recent studies, we use the raw version of the Baker–Wurgler sentiment index that excludes the NYSE turnover variable.

[9] In related work, Moskowitz (2000) shows that actively managed funds perform better during economic recessions when the marginal

utility of wealth is high (see also Avramov and Wermers 2006, Kosowski 2011, and Kacperczyk et al. 2014).

[10] From an empirical standpoint, we estimate the FFC-adjusted alpha in a given month as the difference between the fund return and its realized risk premium, defined as the vector of beta—estimated from a rolling FFC four-factor model for the five years preceding the month in question—times the vector of realized factors for that month. We then compute the average of monthly alpha values of funds within a given quarter.

[11] The annual impact of the fund return is −1.06%, computed as $-2.528\% \times 0.035 \times 12$, where −2.528% is the regression coefficient in Model 1 and 0.035 is the standard deviation of AFO (as reported in Internet Appendix Table IA1).

References

Akbas F, Armstrong WJ, Sorescu S, Subrahmanyam A (2015) Smart money, dumb money, and capital market anomalies. *J. Financial Econom.* 118(2):355–382.

Ali A, Chen X, Yao T, Yu T (2008) Do mutual funds profit from the accruals anomaly? *J. Accounting Res.* 46(1):1–26.

Amihud Y (2002) Illiquidity and stock returns: Cross-section and time-series effects. *J. Financial Marketing* 5(1):31–56.

Amihud Y, Goyenko R (2013) Mutual fund's R^2 as predictor of performance. *Rev. Financial Stud.* 26(3):667–694.

Ang A, Hodrick R, Xing Y, Zhang X (2006) The cross-section of volatility and expected returns. *J. Finance* 61(1):259–299.

Avramov D, Wermers R (2006) Investing in mutual funds when returns are predictable. *J. Financial Econom.* 81(2):339–377.

Avramov D, Chordia T, Jostova G, Philipov A (2013) Anomalies and financial distress. *J. Financial Econom.* 108(1):139–159.

Baker M, Wurgler J (2006) Investor sentiment and the cross-section of stock returns. *J. Finance* 61(4):1645–1680.

Baker M, Wurgler J (2007) Investor sentiment in the stock market. *J. Econom. Perspect.* 21(2):129–151.

Berk JB, van Binsbergen JH (2015) Measuring skill in the mutual fund industry. *J. Financial Econom.* 118(1):1–20.

Campbell JY, Hilscher J, Szilagyi J (2008) In search of distress risk. *J. Finance* 63(6):2899–2939.

Carhart MM (1997) On persistence in mutual fund performance. *J. Finance* 52(1):57–82.

Chen L, Novy-Marx R, Zhang L (2011) An alternative three-factor model. Working paper, Cheung Kong Graduate School of Business, Beijing.

Chen J, Hong H, Huang M, Kubik JD (2004) Does fund size erode mutual fund performance? The role of liquidity and organization. *Amer. Econom. Rev.* 94(5):1276–1302.

Chevalier J, Ellison G (1997) Risk taking by mutual funds as a response to incentives. *J. Political Econom.* 105(6):1167–1200.

Christoffersen SEK, Musto DK (2002) Demand curves and the pricing of money management. *Rev. Financial Stud.* 15(5):1499–1524.

Cooper MJ, Gulen H, Schill MJ (2008) Asset growth and the cross-section of stock returns. *J. Finance* 63(4):1609–1651.

Cremers KJM, Petajisto A (2009) How active is your fund manager? A new measure that predicts performance. *Rev. Financial Stud.* 22(9):3329–3365.

Cremers M, Ferreira MA, Matos P, Starks L (2016) Indexing and active fund management: International evidence. *J. Financial Econom.* 120(3):539–560.

Daniel KD, Titman S (2006) Market reactions to tangible and intangible information. *J. Finance* 61(4):1605–1643.

Daniel K, Grinblatt M, Titman S, Wermers R (1997) Measuring mutual fund performance with characteristic-based benchmarks. *J. Finance* 52(3):1035–1058.

Edelen RM, Ince OS, Kadlec GB (2016) Institutional investors and stock return anomalies. *J. Financial Econom.* 119(3):472–488.

Elton EJ, Gruber MJ, Blake CR (1996) Survivorship bias and mutual fund performance. *Rev. Financial Stud.* 9(4):1097–1120.

Falkenstein EG (1996) Preferences for stock characteristics as revealed by mutual fund portfolio holdings. *J. Finance* 51(1):111–135.

Fama EF (1972) Components of investment performance. *J. Finance* 27(3):551–567.

Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. *J. Financial Econom.* 33(1):3–56.

Fama EF, French KR (2006) Profitability, investment and average returns. *J. Financial Econom.* 82(3):491–518.

Fama EF, MacBeth J (1973) Risk, return, and equilibrium: Empirical tests. *J. Political Econom.* 81(3):607–636.

Frazzini A, Friedman J, Pomorski L (2016) Deactivating active share. *Financial Anal. J.* 72(2):14–21.

Gil-Bazo J, Ruiz-Verdú P (2009) The relation between price and performance in the mutual fund industry. *J. Finance* 64(5):2153–2183.

Gruber MJ (1996) Another puzzle: The growth in actively managed mutual funds. *J. Finance* 51(3):783–810.

Hirshleifer D, Hou K, Teoh SH, Zhang Y (2004) Do investors overvalue firms with bloated balance sheets? *J. Accounting Econom.* 38(December):297–331.

Ibbotson RG, Chen Z, Kim DY-J, Hu WY (2013) Liquidity as an investment style. *Financial Anal. J.* 69(3):30–44.

Idzorek TM, Xiong JX, Ibbotson RG (2012) The liquidity style of mutual funds. *Financial Anal. J.* 68(6):38–53.

Jegadeesh N, Titman S (1993) Returns to buying winners and selling losers: Implications for market efficiency. *J. Finance* 48(1):65–91.

Jiang H, Sun Z (2014) Dispersion in beliefs among active mutual funds and the cross-section of stock returns. *J. Financial Econom.* 114(2):341–365.

Jiang H, Zheng L (2018) Active fundamental performance. *Rev. Financial Stud.* 31(12):4688–4719.

Kacperczyk M, Sialm C, Zheng L (2005) On the industry concentration of actively managed equity mutual funds. *J. Finance* 60(4):1983–2012.

Kacperczyk M, Sialm C, Zheng L (2008) Unobserved actions of mutual funds. *Rev. Financial Stud.* 21(6):2379–2416.

Kacperczyk M, Van Nieuwerburgh S, Veldkamp L (2014) Time-varying fund manager skill. *J. Finance* 69(4):1455–1484.

Kogan L, Tian M (2015) Firm characteristics and empirical factor models: A model-mining experiment. Working paper, Massachusetts Institute of Technology, Cambridge.

Korajczyk RA, Sadka R (2004) Are momentum profits robust to trading costs? *J. Finance* 59(3):1039–1082.

Kosowski R (2011) Do mutual funds perform when it matters most to investors? US mutual fund performance and risk in recessions and expansions. *Quart. J. Finance* 1(3):607–664.

Kozak S, Nagel S, Santosh S (2018) Interpreting factor models. *J. Finance* 73(3):1183–1223.

Loughran T, Ritter JR (1995) The new issues puzzle. *J. Finance* 50(1):23–51.

Malkiel BG (1995) Returns from investing in equity mutual funds 1971 to 1991. *J. Finance* 50(2):549–572.

Miller EM (1977) Risk, uncertainty, and divergence of opinion. *J. Finance* 32(4):1151–1168.

Moskowitz TJ (2000) Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. (Discussion.) *J. Finance* 55(4):1695–1703.

Newey WK, West KD (1987) A simple positive-definite heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55(3):703–708.

Novy-Marx R (2013) The other side of value: The gross profitability premium. *J. Financial Econom.* 108(1):1–28.

Ohlson JA (1980) Financial ratios and the probabilistic prediction of bankruptcy. *J. Accounting Res.* 18(1):109–131.

Pástor L, Stambaugh RF, Taylor LA (2017) Do funds make more when they trade more? *J. Finance* 72(4):1483–1528.

Petajisto A (2013) Active share and mutual fund performance. *Financial Anal. J.* 69(4):73–93.

Ritter JR (1991) The long-run performance of initial public offerings. *J. Finance* 46(1):3–27.

Sloan RG (1996) Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting Rev.* 71(3):289–315.

Stambaugh RF, Yuan Y (2017) Mispricing factors. *Rev. Financial Stud.* 30(4):1270–1315.

Stambaugh RF, Yu J, Yuan Y (2012) The short of it: Investor sentiment and anomalies. *J. Financial Econom.* 104(2):288–302.

Stambaugh RF, Yu J, Yuan Y (2015) Arbitrage asymmetry and the idiosyncratic volatility puzzle. *J. Finance* 70(5):1903–1948.

Titman S, Wei K, Xie F (2004) Capital investments and stock returns. *J. Financial Quant. Anal.* 39(4):677–700.

Wermers R (2000) Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. *J. Finance* 55(4):1655–1695.

Wermers R (2003) Are mutual fund shareholders compensated for active management "bets"? Working paper, University of Maryland, College Park, College Park.