A Test of the Self-Serving Attribution Bias: Evidence from Mutual Funds

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Abstract

This paper studies the dynamics of investor overconfidence. Using the sum of absolute deviations from one's benchmark index (i.e., Active Share) as a proxy for confidence, we show that the average mutual fund manager tends to boost his confidence to a larger extent after receiving confirming public signals than to decrease it after disconfirming public signals. This bias is stronger among inexperienced managers and is largely absent among experienced ones. The bias also leads to poor future performance, the majority of which is driven by managers' sub-optimal portfolio choices. In dissecting managers' portfolio choices, we further document that the underperformance resulting from biased attribution is potentially due to managers' increasingly active stock picks in industries that they are less familiar with.

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1 Introduction

Recent empirical studies find that agents' overconfident beliefs (i.e., attaching too high precisions to their private signals) could lead to sub-optimal decisions. For example, Barber and Odean (2000, 2001, 2002) document that individual investors trade excessively despite earning negative returns net of transaction costs. Using late option exercising as a measure of managers' overconfidence, Malmendier and Tate (2005, 2008) and Malmendier, Tate, and Yan (2010) find that managerial overconfidence can, in part, explain value-destroying investment, merger and acquisition, and financing decisions. Despite the extensive literature on the consequences of overconfident behavior, it is still unclear how these overconfident beliefs are formed. Is overconfidence a personal trait or do agents gain excessive confidence over time, perhaps from their past experiences?

Two theoretical papers, Daniel, Hirshleifer, and Subrahmanyam (1998) and Gervais and Odean (2001), study the evolution of agents' overconfidence by formally introducing a well-established behavioral bias, the self-serving attribution bias, into standard learning models. The bias states that people tend to attribute successes to their own skills but failures to bad luck (or other external factors).[1] More specifically, when agents can only learn about the unobserved quality of their private signals through noisy feedbacks, they tend to overestimate their ability to gather and process information, and revise the perceived precisions of their private signals upward too much, relative to the Bayesian benchmark, upon observing confirming public signals. In contrast, they revise their perceived precisions downward too little with disconfirming public signals. Agents therefore accumulate unwarranted confidence after receiving a number of confirming and disconfirming public signals, which can be purely due to luck. Investors in financial markets are particularly susceptible to the self-serving attribution bias, as investment decisions can only be verified with vague and delayed feedbacks.

This paper is one of the first empirical attempts to bring the biased-attribution hypothesis to the data.[2] We formalize our test hypotheses in a simple stylized model in the spirit

[1] For evidence on the self-serving attribution bias from the psychology literature, see, for example, Wolosin, Sherman, and Till (1973); Langer and Roth (1975); Miller and Ross (1975).

[2] Hilary and Menzly (2006) and Hilary and Hsu (2010) analyze how past accuracy of analyst and managerial earnings forecasts influence the accuracy of their subsequent forecasts. Glaser and Weber (2009) further document that past portfolio returns positively affect retail investors' subsequent trading intensity. Chui,

of Daniel, Hirshleifer, and Subrahmanyam (1998). An informed agent receives a private signal on the liquidating value of a stock, subsequently updates the perceived precision of his private signal based on the realizations of a series of public signals, and chooses his portfolios accordingly. We depart from the Bayesian benchmark by assuming that the informed agent suffers from the self-serving attribution bias. Specifically, when the agent experiences a positive benchmark-adjusted return, i.e., his private signal is confirmed by a subsequent public signal, he significantly inflates the perceived precision of his private signal; in contrast, a negative benchmark-adjusted return only mildly deflates his confidence.

The main testable implication of our stylized model is that, at the end of T periods, the deviation of the agent's portfolio from his benchmark index (labeled Active Share), which reflects the agent's (over)confidence in his private signal, is monotonically increasing in both the total benchmark-adjusted portfolio return and the sum of positive benchmark-adjusted portfolio returns (SPR) over the T periods.[3] While the former effectively captures the updating rule with disconfirming public signals, the latter reflects the agent's differential reactions to confirming and disconfirming public signals. A positive relation between Active Share and SPR is thus evidence of biased attribution.

We test this prediction by examining the portfolio choices and trading behavior of a particular group of agents – active mutual fund managers, for whom we have detailed and comprehensive data on their investment decisions and realized performance. Since a month (or a quarter) is a natural horizon for performance evaluation, we conjecture that a typical mutual fund manager maintains a separate mental account for his performance in each month (quarter) and updates the perceived precisions of his investment signals accordingly. More specifically, we construct a measure $SPR_{i,t}$, for each mutual fund i at the end of each month t, by summing up all positive monthly benchmark-adjusted returns in the previous year.[4] We use benchmark-adjusted rather than raw fund returns in our variable construction because

Titman, and Wei (2010) use an individualism index, which they argue is related to overconfidence and biased attribution, to examine returns to momentum strategies around the world.

[3]The Active Share of a portfolio, introduced by Cremers and Petajisto (2009), describes the extent to which the portfolio deviates from its benchmark index. For example, an Active Share of 30% indicates that the agent invests 30% in a long-short active portfolio on top of tracking his benchmark index.

[4]We also construct SPR using quarterly fund returns and obtain similar results. In addition, our results are qualitatively unchanged if we sum up all positive monthly benchmark-adjusted returns in the previous quarter, six months, two years, or three years instead. We have also tried different weighting schemes, for example, to give more weights to more recent months, and the results are similar.

an uninformed manager (or one who thinks he is uninformed) can earn benchmark returns by simply tracking the index.

To isolate the effect of SPR from other confounding factors that may influence managers' portfolio choices, as summarized by Active Share, we control for the tracking error, turnover ratio, fund flows, among many other observable fund characteristics in our full test specification. In addition, as our simple model suggests, we also control for the total benchmark-adjusted fund return over the same horizon as SPR. We argue that the residual effect of lagged SPR on changes in Active Share reflects managers' biased-attribution.

Our results are consistent with the biased-attribution hypothesis. The effect of lagged SPR on (changes in) Active Share is economically and statistically significant. A one-standard-deviation increase in SPR, *ceteris paribus*, leads to increases in Active Share by 0.55% (t=2.49) and 0.42% (t=2.01) in the following two quarters, which are similar in magnitude to the average change in Active Share over a quarter. We also find that the tendency to self-attribute is significantly more pronounced for less experienced managers. We measure experience using both the number of years a manager has been in the mutual fund industry and the number of years a mutual fund has been in existence.[5] The coefficient on SPR in the bottom half is significantly higher than that in the top half when managers are ranked by either experience measure. Managers in the top half are virtually unaffected by the bias, suggesting that experience can help alleviate the attribution bias.

Moreover, if mutual fund managers are subject to the self-serving attribution bias, i.e., accumulating unwarranted confidence in response to SPR, and thus make sub-optimal investment decisions and trade excessively thereafter, they should experience deteriorating future performance with a high SPR. We find supportive evidence for this prediction in the data. SPR significantly and negatively predicts risk-adjusted fund performance and the associated information ratios in the next one to three years. For example, a one-standard-deviation increase in SPR leads to a reduction in annual abnormal fund returns by 78 basis points (t=-2.42) and a reduction in annualized information ratio by 9.96% (t=-3.09)in the following three years.

To examine the extent to which this reduction in abnormal performance is due to

[5]The second measure is motivated by prior studies that use long-term fund returns as a measure of manager ability (e.g., Carhart (1997) and Cohen, Coval, and Pastor (2005)).

poor portfolio choices or excessive trading, we conduct additional performance tests using holdings-based mutual fund returns. Assuming that mutual funds do not change their positions between two reporting dates, we calculate a hypothetical series of fund returns based on these reported holdings. A one-standard-deviation increase in SPR leads to a decrease in annual abnormal holdings-based returns by 57 basis points (t=-2.03) and a decrease in annualized information ratio by 7.71% (t=-2.36). These findings imply that around three quarters of the underperformance resulting from biased attribution is likely caused by managers' poor portfolio choices, while the remaining quarter is due to trading costs and unobserved fund actions. These results also imply that mutual fund managers do not get infinitely overconfident under the influence of biased attribution: Overconfident managers on average underperform their peers, which in turn lowers their confidence in their private signals.

To provide further details on the exact changes in portfolio choice as a function of SPR, we decompose Active Share into two parts: Across-Industry Active Share ($AIAS$) and Within-Industry Active Share ($WIAS$). The former measures a portfolio's deviation in industry weight from its benchmark index, while the latter measures the average deviation in individual stock weight within each industry from the benchmark. Such a decomposition is motivated by the finding of Kacperczyk, Sialm, and Zheng (2005) that fund managers have stock picking ability concentrated in a few industries. Consistent with the findings in Kacperczyk, Sialm, and Zheng (2005), we show that the performance predictability of Active Share is largely contributed by its across-industry component, yet managers substantially increase their $WIAS$, but not their $AIAS$, in response to lagged SPR. In addition, we find that managers tend to increase their $WIAS$ in industries they underweight relative to their benchmark indices. One possible interpretation is that, while managers possess stock-picking skills in a few industries, they become more active stock pickers in all industries and particularly industries they previously underweight (i.e., those they are less familiar with), as they get overconfident and therefore underperform subsequently.

The findings of this paper complement the recent literature on the effect of biased attribution on financial markets (e.g., Hilary and Menzly (2006), Glaser and Weber (2009), Chui, Titman, and Wei (2010), and Hilary and Hsu (2010)). The contributions of this paper are twofold. First, it shows that mutual fund managers, who are perceived by academic researchers as savvy arbitrageurs, are also subject to behavioral biases. In particular, this paper is among the first to show that mutual fund managers may be overconfident. Second, we provide more direct evidence for the biased-attribution hypothesis: Unlike prior studies that examine the relation between agents' past performance and subsequent overconfident behavior, which is confounded by many other factors and could be consistent with Bayesian updating, we directly examine agents' differential responses to confirming and disconfirming public signals by focusing on the SPR measure.

Our paper is also related to a contemporaneous study by Huang, Sialm, and Zhang (2010), who document a negative relation between an increase in a mutual fund's risk level and its subsequent performance. This paper can be seen as offering a complementary explanation for the negative correlation documented in Huang, Sialm, and Zhang (2010). When managers get overconfident, they become more active in their portfolio decisions, potentially increase their risk exposure, and subsequently underperform.

The remainder of the paper is organized as follows. Section 2 describes the data sample and the screening procedures. Section 3 presents a simple model of biased updating. Section 4 presents evidence of self-serving attribution bias and its relation to future fund performance. Section 5 analyzes across-industry and within-industry portfolio choices. Section 6 conducts robustness tests, and finally, Section 7 concludes.

2 Data

2.1 Mutual Fund Data

Mutual fund holdings data are obtained from Thomson Reuters Mutual Fund Holdings database (formerly known as CDA/Spectrum). We focus on the period 1985 – 2006, because there were relatively few actively managed mutual funds in the early 1980s.[6] The database is compiled from mandatory SEC filings as well as voluntary disclosures by mutual funds. Most mutual funds in the database report their holdings on a quarterly basis. Although every fund files its report at the end of a quarter, the date for which the holdings are valid (report date) is often different from the filing date. In some cases, the two dates can differ

[6]For robustness, we also start our sample period in years 1980 and 1990 and obtain similar results.

by a few quarters. Since the number of shares reported in Thomson is split-adjusted as of the filing date, to get the actual number of shares held on the report date, we reverse the adjustment done by Thomson. Next, to compute the shares held by each mutual fund at each quarter-end, we adjust the reported number of shares for stock splits between the report date and quarter end.

Total net assets (TNA), monthly returns, expense ratios, objective codes, and fund age are obtained from the CRSP mutual funds database. We use pre-expense fund returns in our study, i.e., net returns plus 1/12 of annual expenses.[7] For funds with multiple share classes reported in CRSP, we use the sum of total net assets of all share classes as the fund size, and the value-weighted average return across all share classes as the fund return. For other fund characteristics, we use the value of the share class with the largest size. We then use Mutual Fund Links (MFLinks) to merge Thomson Reuters mutual fund holdings data with the CRSP mutual fund database.

Since our focus is on domestic equity funds, we further require each fund to have a Wiesenberger objective code of growth, growth and income, equity income, growth with current income, maximum capital gains, small capitalization growth, or missing. We also require an ICDI fund objective code of aggressive growth, growth and income, income, long-term growth, or missing. Finally, we require the investment objective code reported by Thomson to be aggressive growth, growth, growth and income, unclassified, or missing. These restrictions effectively exclude all bond funds, balanced funds, international funds, precious metals, and sector funds. We also exclude index funds from our sample by removing any mutual fund whose name contains "index," "indx," or "idx."

Since a significant fraction of mutual funds misclassifies themselves as equity funds, we compute the weight of its stock holdings as a percentage of its total net assets for each fund on each report date. We require the time-series average equity weight to be greater than 80%. Finally, to be included in the sample, we require a fund to have non-missing values for all variables used in the main regression analysis.[8] With the aforementioned screening procedures, we end up with a sample of 46,510 fund-quarter observations and 2,380 distinct

[7]Monthly returns reported by CRSP are net returns, i.e., after fees, expenses, and brokerage commissions but before any front-end and back-end loads.

[8]The list of variables includes Delta Active Share, SPR, benchmark-adjusted returns, tracking errors, fund age, size, flows, unrealized gains, turnover, and annual expenses.

mutual funds.

2.2 Benchmark Indices

We include 23 commonly tracked indices from three major US index families in our study. From the S&P/Barra family, we pick S&P 500, S&P500/Barra Growth, S&P500/Barra Value, S&P 400, S&P400/Barra Growth, S&P400/Barra Value, S&P 600, S&P600/Barra Growth, and S&P600/Barra Value. From the Russell index family, we include Russell 2000, Russell 2000 Growth, Russell 2000 Value, Russell 1000, Russell 1000 Growth, Russell 1000 Value, Russell 3000, Russell 3000 Growth, Russell 3000 Value, Russell Midcap, Russell Midcap Growth, and Russell Midcap Value. Finally, we also include two popular Wilshire indices: Wilshire 4500 and Wilshire 5000. Index holdings data are obtained directly from the companies that manage those indices. We have month-end index membership for most indices in our sample period.

Although mutual funds are required by the SEC to report their benchmark indices in their prospectus after 1998, such data are not available in any public database. Following Cremers and Petajisto (2009), we compute the Active Share of a fund (discussed in the next subsection) with respect to all available indices and pick the index with the smallest Active Share as its benchmark. By construction, this index has the most overlap with the fund holdings.[9] If an index is unavailable (e.g., the Russell indices started in the late 1980s) or its constituents are unknown in a certain month, we use the remaining indices to compute the benchmark for each fund in that month.

2.3 Active Share and Delta Active Share

Cremers and Petajisto (2009) propose a novel measure, which they label Active Share, to quantify active portfolio management. Active Share is defined as one half of the sum of

[9]The Morningstar database also computes its own benchmarks, by picking the index with the smallest tracking error.

absolute deviations in portfolio weight of a mutual fund portfolio from its benchmark index:

$$ActiveShare = \frac{1}{2}\sum_{n=1}^{N} |w_n^{mgr} - w_n^{index}|, \tag{1}$$

where w_n^{mgr} and w_n^{index} are, respectively, the portfolio weight of stock n in the manager's portfolio and that in its benchmark index, and N is the total number of stocks in CRSP monthly stock files.[10] Consider the following simple example: A mutual fund invests 30% of its total net asset in stock A and 70% in stock B, while its benchmark index invests 40% in A and 60% in B. The fund's Active Share is then equal to 1/2 * (|30% - 40%|+ |70% - 60%|) = 10%. One appealing feature of this measure is its easy interpretation. With an Active Share of 10%, the fund can be viewed as investing 100% of its total net assets in the benchmark index and, in the meanwhile, taking a side bet of 10% in a self-financed long-short *active portfolio*. In the above example, the active portfolio is 100% short in stock A and 100% long in stock B.[11]

Note that when there are more than two stocks in the benchmark index, managers with the same Active Share can have different active portfolios given their private signals. Thus, while the Active Share measure captures the extent to which a manager is willing to take on his side bet, it does not describe the risk characteristic of that particular side bet. Other measures proposed in the literature, e.g., the tracking error, better reflect such risk characteristic. We motivate our choice to focus on Active Share in our stylized model in Section 3.

Finally, it can be seen that Active Share varies as stock prices (and thus portfolio weights) fluctuate even in the absence of trading. We explicitly eliminate such mechanical changes in our construction of Delta Active Share (ΔAS). Delta Active Share in quarter t is defined as the logarithm of Active Share of a manager's reported portfolio at the end of quarter t minus that of a hypothetical portfolio had the manager *not* traded in quarter t. By construction, this measure captures the change in Active Share that is entirely due to active trading taking place in quarter t.

[10] All variables in this section are calculated for each fund in each quarter. When there is no confusion, we suppress the fund and time subscripts for brevity.

[11] To provide further insights on managers' investment decisions, we introduce Across-Industry Active Share and Within-Industry Active Share in Section 5. The measures are defined similarly using portfolio weights of industries and those of stocks within industries, respectively.

2.4 Other Variables

We also construct a list of other variables to address potential alternative stories. For example, following prior studies, e.g., Chevalier and Ellison (1997) and Sirri and Tufano (1998), we compute quarterly mutual fund flows as:

$$FLOW_t = TNA_t - TNA_{t-1} * (1 + r_t) - MGN_t, \tag{2}$$

where r_t is the fund's return in quarter t, and MGN is the increase in TNA (Total Net Assets) due to fund mergers in quarter t. Implicitly, we assume that inflows and outflows occur at the end of a quarter, and investors reinvest their dividends and capital appreciation distributions in the fund. We further assume that after a merger, investors place all their money in the surviving fund.

To control for the potential impact of the disposition effect, we calculate the average purchase price for each position in each manager's portfolio, and compute the unrealized gain as the percentage change in the current value over the average purchase value. For example, if a fund purchases 10 shares of stock A at $10 and later purchases another 10 shares at $20, we take the average, i.e., $15/share, as the base purchase price. If today's stock price is $30, the unrealized gain is then ($30-$15)/$15 = 100%.

2.5 Summary Statistics

Table 1 reports the summary statistics of Active Share, fund returns, and other observable fund characteristics. Comparable to the figures presented in Cremers and Petajisto (2009), the average Active Share across all mutual funds is close to 80%, and the standard deviation is about 17%. Quarterly changes in Active Share are slightly negative on average, with a mean (median) of -0.7% (-0.1%), which is likely due to rebalancing concerns.[12] There is, however, substantial heterogeneity across mutual funds: the standard deviation of quarterly changes in Active Share is almost 8%. Consistent with prior literature on mutual fund performance evaluation, our sample of mutual funds does not outperform their corresponding benchmark

[12]Unreported numerical simulation results indicate that, with mild fund returns, rebalancing always decreases Active Share.

indices. The average benchmark-adjusted return (before fees and expenses) over a year is about 50bp. Given that the average expense ratio in our sample is around 1.3%, the average net-of-fee benchmark-adjusted return of the mutual fund industry is about -80bp a year. The average annual investment flow, average fund age, and average fund size of our sample are 11% of total net assets, 14 years, and $1.03 billion, respectively, all of which are in line with prior studies. The main variable of the study, SPR over a year, has a mean of 9.8% and a standard deviation of 9.1%. SPR is also slightly positively skewed, as it has a lower bound of 0.

3 A Stylized Model

3.1 Model Setup

We formalize the dynamics of investor overconfidence and derive its effects on investors' portfolio choices in a simple stylized model. The setup of the model is borrowed extensively from Daniel, Hirshleifer, and Subrahmanyam (1998). The economy is populated with a continuous mass of agents. A fraction ω of these agents is informed, denoted by I and the remaining fraction 1-ω is uninformed, denoted by U. For tractability, we assume that both I and U have the same exponential utility function defined on their terminal period consumption, with an absolute risk aversion coefficient γ.

There are two risky securities (A and B) with independent payoffs in the market, as well as a riskless asset, whose return is normalized to zero. The informed agents receive a common private signal about the payoff of security A. We include security B in the economy so that it is meaningful to think about portfolio weights and possible deviations from the market portfolio. For simplicity, we assume that both risky assets have a fixed supply of $1, so that the market portfolio invests equally in both assets. There are three dates in the model. At date 1, I receives a common private signal s_1. Both I and U choose their optimal portfolios, and security prices adjust to clear the market. At date 2, a noisy public signal is released. Further trade occurs and prices adjust accordingly. At date 3 (the terminal date), the final payoffs are announced, both securities pay their liquidating dividends, and agents consume. All random variables in the model are independently and normally distributed.

The final payoffs of securities A and B are denoted by θ_A and θ_B, which are assumed to be independently and normally distributed with mean $\overline{\theta}_A$ and $\overline{\theta}_B$ and with variance $\frac{1}{\beta_{\theta,A}}$ and $\frac{1}{\beta_{\theta,B}}$, respectively. Without loss of generality, we set both $\overline{\theta}_A$ and $\overline{\theta}_B$ to zero. I receives a private signal about θ_A at date 1, $s_1 = \theta + \epsilon$, where $\epsilon \sim N(0, \frac{1}{\beta_\epsilon})$. The perceived noise variance of s_1 by I is $\frac{1}{\beta_c}$. We assume I has the correct belief about β_ϵ at date 1, i.e., $\beta_c = \beta_\epsilon$. For simplicity, we further assume that, while the information structure is common knowledge to both I and U, the uninformed do not learn about s_1 from prices.[13]

At date 2, a public signal arrives, $s_2 = \theta + \eta$, where $\eta \sim N(0, \frac{1}{\beta_\eta})$. Following Daniel, Hirshleifer, and Subrahmanyam (1998), we assume that I is subject to the self-serving attribution bias when learning about the precision of his private signal. More specifically, if the public signal announced at date 2 confirms his trade at date 1, the agent becomes more confident; if it disconfirms his trade, the agent becomes less confident, but to a less extent. Formally, we assume that the precision of the private signal perceived by I depends on the realization of the public signal at date 2. If $sign(s_1) = sign(s_2)$, confidence increases, so the self-perceived noise variance in the private signal decreases to $\frac{1}{\overline{\beta}_{c,2}} = (1 - \overline{k})\frac{1}{\beta_c}$. If $sign(s_1) \neq sign(s_2)$, confidence decreases, so the self-perceived noise variance in the signal increases to $\frac{1}{\underline{\beta}_{c,2}} = (1 + \underline{k})\frac{1}{\beta_c}$. We further assume, without going into details, that a Bayesian agent would update his perceived noise variance to $\frac{1}{\beta_{Bayesian}} = (1 \pm k_{Bayesian})\frac{1}{\beta_c}$, if the public signal confirms or disconfirms his private signal. The key assumption of our model is that $\overline{k} > k_{Bayesian} > \underline{k}$. $\overline{k} - \underline{k}$ therefore captures the degree of an investor's self-serving attribution bias.

3.2 The Benchmark Case

We first study the benchmark case, where agents do not suffer from the self-serving attribution bias, i.e. the perceived noise variance is $\frac{1}{\beta_{Bayesian}}$ at date 2. This case outlines how we solve for the equilibrium prices and demands. Prices at date 3 are given by the final payoffs of A and B: $P_3^A = \theta_A$ and $P_3^B = \theta_B$. Because all random variables follow normal distributions and agents have exponential utility functions, by standard portfolio theories,

[13] These two assumptions are not critical. The initial value of β_c has no impact on the predictions of the model, and the main predictions of the model will hold in a noisy learning framework.

the demand for security A at date 2 is:

$$D_{I,2}^A = \frac{E[\theta_A|s_1, s_2] - P_2^A}{\gamma\sigma^2[\theta_A|s_1, s_2]}, \tag{3}$$

$$D_{U,2}^A = \frac{E[\theta_A|s_2] - P_2^A}{\gamma\sigma^2[\theta_A|s_2]}, \tag{4}$$

where $D_{I,2}^A$ is the demand by agent I and $D_{U,2}^A$ is the demand by agent U at date 2. Under Bayesian updating,

$$E[\theta_A|s_1, s_2] = \frac{s_1\beta_{Bayesian} + s_2\beta_\eta}{\beta_{\theta,A} + \beta_{Bayesian} + \beta_\eta}, \tag{5}$$

$$\sigma^2[\theta_A|s_1, s_2] = \frac{1}{\beta_{\theta,A} + \beta_{Bayesian} + \beta_\eta}, \tag{6}$$

$$E[\theta_A|s_2] = \frac{s_2\beta_\eta}{\beta_{\theta,A} + \beta_\eta}, \tag{7}$$

$$\sigma^2[\theta_A|s_2] = \frac{1}{\beta_{\theta,A} + \beta_\eta}. \tag{8}$$

Applying the market clearing condition (i.e., $\omega D_I + (1-\omega)D_U = 1$), we have

$$P_2^A = \frac{\omega s_1\beta_{Bayesian} + s_2\beta_\eta - \gamma}{\omega\beta_{Bayesian} + \beta_{\theta,A} + \beta_\eta}. \tag{9}$$

Therefore,

$$D_{I,2}^A = \frac{(1-\omega)(s_1\beta_{Bayesian}(\beta_{\theta,A} + \beta_\eta) - s_2\beta_{Bayesian}\beta_\eta) + \gamma(\beta_{Bayesian} + \beta_{\theta,A} + \beta_\eta)}{\gamma(\omega\beta_{Bayesian} + \beta_{\theta,A} + \beta_\eta)}, \tag{10}$$

$$D_{U,2}^A = \frac{-\omega(s_1\beta_{Bayesian}(\beta_{\theta,A} + \beta_\eta) - s_2\beta_{Bayesian}\beta_\eta) + \gamma(\beta_{\theta,A} + \beta_\eta)}{\gamma(\omega\beta_{Bayesian} + \beta_{\theta,A} + \beta_\eta)}. \tag{11}$$

For security B, since there is no additional information released about its terminal payoff, its demand and price at date 2 are:

$$D_{I,2}^B = D_{U,2}^B = \frac{E[\theta_B] - P_2^B}{\gamma\sigma^2[\theta_B]} = 1. \tag{12}$$

3.3 Equilibrium Prices with the Bias

We now characterize the market equilibrium when I is subject to the self-serving attribution bias. Compared to the benchmark case, the agent's perceived noise variance at date 2 is no longer $\frac{1}{\beta_{Bayesian}}$, but rather $\frac{1}{\beta_{c,2}}$. If $sign(s_1) = sign(s_2)$,

$$D^A_{I,2} = \frac{(1-\omega)(s_1\overline{\beta}_{c,2}(\beta_{\theta,A}+\beta_\eta) - s_2\overline{\beta}_{c,2}\beta_\eta) + \gamma(\overline{\beta}_{c,2}+\beta_{\theta,A}+\beta_\eta)}{\gamma(\omega\overline{\beta}_{c,2}+\beta_{\theta,A}+\beta_\eta)}, \tag{13}$$

where $\frac{1}{\overline{\beta}_{c,2}} = (1-\overline{k})\frac{1}{\beta_c} < \frac{1}{\beta_{Bayesian}}$. If $sign(s1) \neq sign(s2)$,

$$D^A_{I,2} = \frac{(1-\omega)(s_1\underline{\beta}_{c,2}(\beta_{\theta,A}+\beta_\eta) - s_2\underline{\beta}_{c,2}\beta_\eta) + \gamma(\underline{\beta}_{c,2}+\beta_{\theta,A}+\beta_\eta)}{\gamma(\omega\underline{\beta}_{c,2}+\beta_{\theta,A}+\beta_\eta)}, \tag{14}$$

where $\frac{1}{\underline{\beta}_{c,2}} = (1+\underline{k})\frac{1}{\beta_c} > \frac{1}{\beta_{Bayesian}}$. The prices at date 3 are again determined by the liquidating payoffs of the two securities.

3.4 Empirical Implications

Since our goal is to understand whether agents suffer from biased attribution, rather than deriving implications for agents' unconditional overconfidence (e.g., Gervais and Odean (2001)), we examine how a series of realizations of public signals can affect an agent's confidence and thus his portfolio choice. To this end, we extend our model to span T+2 periods, with T public signals (i.i.d.) being released before the liquidating dividend is distributed. Denote the average public signal over the T periods by $\overline{s}$. Upon the realization of each public signal, I adjusts the perceived precision of his private signal using the biased updating rule. For simplicity, we further assume that $\overline{k}$ and $\underline{k}$ remain constant in all periods. The deviation of agent I's portfolio from the market portfolio, which invests \$1 in both assets, at date T+1 is given by

$$D^A_{I,T+1} - 1 = \frac{(1-\omega)\beta_{c,T+1}(s_1(\beta_{\theta,A}+T\beta_\eta) - \overline{s}T\beta_\eta + \gamma)}{\gamma(\omega\beta_{c,T+1}+\beta_{\theta,A}+T\beta_\eta)}, \tag{15}$$

$$D^B_{I,T+1} - 1 = 0, \tag{16}$$

where

$$\frac{1}{\beta_{c,T+1}} = \frac{1}{\beta_c}(1-\overline{k})^{n^+}(1+\underline{k})^{n^-}. \tag{17}$$

n^+ is the number of periods in which $sign(s_1) = sign(s_t)$, and $n^- = T - n^+$ is the number of periods in which $sign(s_1) \neq sign(s_t)$.

We next analyze the relation between Active Share and managerial overconfidence. We use Active Share, rather than tracking errors, as our main measure of activeness, because tracking errors are determined jointly by a manager's Active Share and the volatility of his active portfolio. The latter in turn depends on other factors, such as stock return correlations and the information structure. As a result, there is no clear relation between tracking errors and managerial confidence.

The Active Share of I's portfolio, defined as one half of the sum of absolute deviations of I's portfolio weights from the market portfolio, can be written as

$$\begin{aligned} ActiveShare_{I,T+1} &= \frac{1}{2}(|\frac{1}{2} - \frac{D^A_{I,T+1}}{D^A_{I,T+1}+D^B_{I,T+1}}| + |\frac{1}{2} - \frac{D^B_{I,T+1}}{D^A_{I,T+1}+D^B_{I,T+1}}|) && (18)\\ &= |\frac{D^A_{I,T+1}-1}{D^A_{I,T+1}+1}|. && (19) \end{aligned}$$

It can be readily shown that $ActiveShare_{I,T+1}$ is monotonically decreasing in the perceived noise variance $\frac{1}{\beta_{c,T+1}}$, and thus is monotonically increasing in $n^+\overline{k} - n^-\underline{k}$ (which can be seen by taking the natural log of the right hand side of equation (17)), as long as $D^A_{I,T+1}$ is greater than -1.[14] Put differently, managers that attach higher precisions to their private signals deviate from their benchmark indices to a larger extent. With some simple algebra, we can write:

$$n^+\overline{k} - n^-\underline{k} = \underbrace{(\overline{k}-\underline{k})n^+}_{1} + \underbrace{\underline{k}(n^+ - n^-)}_{2}. \tag{20}$$

The first term in (20) $(\overline{k}-\underline{k})n^+$ captures the magnitude of biased attribution, while the second term reflects the updating rule when managers receive disconfirming public signals.

Proposition 1. *The Active Share of a portfolio is a monotonically increasing function of* $(\overline{k}-\underline{k})n^+ + \underline{k}(n^+ - n^-)$.

[14] If $D^A_{I,T+1} \leq -1$, the total portfolio value is non-positive, which renders portfolio weights meaningless. We think this is a reasonable assumption as mutual funds rarely engage in short-selling.

Since we do not observe agents' private signals, nor the full set of public information available in the market, to empirically test Proposition 1, we use realized fund returns to proxy for whether subsequent public signals confirm or disconfirm an agent's private signals. Since the decision to deviate from one's benchmark portfolio is based solely on his private signals, a positive benchmark-adjusted return indicates that his private signals are confirmed by subsequently released public information; in contrast, a negative benchmark-adjusted return indicates otherwise. In other words, we can interpret n^+ (n^-) as the number of periods in which an agent has superior (inferior) returns compared to his benchmark.

While our highly stylized model assumes that the degree of the attribution bias ($\overline{k}$ vs. $\underline{k}$) is only dependent on the signs of public and private signals, a more realistic assumption is that both $\overline{k}$ and $\underline{k}$ are functions of how strongly a public signal confirms or disconfirms an agent's private signal. To reflect this additional twist on our model, we use the sum of outperformance in place of n^+ and the absolute sum of underperformance in place of n^-. Equation (20) can then be rewritten as

$$n^+\overline{k} - n^-\underline{k} = \underbrace{(\overline{k} - \underline{k}) * SPR}_{1} + \underbrace{\underline{k} * sumret}_{2}, \tag{21}$$

where

$$SPR = \sum_{ret_{I,t} \geq 0} ret_{I,t} \tag{22}$$

$$sumret = \sum_{ret_{I,t} \geq 0} ret_{I,t} - \sum_{ret_{I,t} < 0} |ret_{I,t}| = \sum_{ret_{I,t} \geq 0} ret_{I,t} + \sum_{ret_{I,t} < 0} ret_{I,t}. \tag{23}$$

We label the first term SPR because it measures the Sum of (all) Positive (Abnormal) Returns in the entire period. The second term, on the other hand, captures the sum of benchmark-adjusted returns over the same period. A positive relationship between Active Share and SPR, after controling for $sumret$, is thus evidence of the self-serving attribution bias. A Bayesian, in constrast, has $\overline{k} = k_{Bayesian} = \underline{k}$ and his Active Share is not increasing in SPR.

Finally, for simplicity, we assume in our model that a portfolio manager only gets overconfident about a particular private signal after receiving confirming public signals. Another plausible assumption is that the manager gets overconfident about his information source or about his way of collecting and processing information. To illustrate the difference, consider a manager that derives a buy signal on Microsoft from reading some news reports. After observing a subsequent rise in Microsoft's stock price, the manager then becomes increasingly (or perhaps excessively) confident in all future signals generated in the same way, rather than only perceiving the particular signal on Microsoft as being more accurate. This extension, while not formally modeled in our paper, allows us to think about the effect of biased attribution on subsequent turnover and other trading characteristics. We defer our discussion on turnover to Section 6.

4 The Dynamics of Manager Overconfidence

This section empirically tests the biased attribution hypothesis. Motivated by the stylized model in the last section, we analyze the impact of biased attribution, as captured by the sum of positive benchmark-adjusted returns (SPR) in the previous year, on investors' subsequent portfolio choices, as reflected in their Active Share. We focus on open-end mutual fund managers in our analyses for two reasons. First, we have detailed and comprehensive data on their investment decisions and realized performance. Second and more importantly, existing evidence on professional money managers' overconfident behavior is, at best, weak.

4.1 Regression Specification

To test the effect of SPR on Active Share, we conduct the following panel regression:

$$\Delta AS_{i,t} = \alpha + \beta_1 * SPR_{i,t-4:t-1} + \beta_2 * sumret_{i,t-4:t-1} + \gamma * CONTROL. \tag{24}$$

The dependent variable in the regression, $\Delta AS_{i,t}$, is the change in Active Share of mutual fund i in quarter t that is purely driven by active trading. Put differently, $\Delta AS_{i,t}$ is the difference between the Active Share from reported holdings at the end of quarter t and the Active Share based on a hypothetical portfolio had the manager not traded in quarter t. A positive ΔAS thus reflects a manager's discretion to deviate more from his benchmark index, while a negative ΔAS indicates otherwise.

The main variable of interest on the right hand side of the equation is $SPR_{i,t-4:t-1}$, which is defined as the sum of positive benchmark-adjusted monthly returns in the previous twelve months.[15] We conjecture that a typical mutual fund manager has a separate mental account for each monthly return and treats it as a separate confirming signal. We focus on benchmark-adjusted rather than raw mutual fund returns, because the former measures the performance of the manager's active portfolio, which in turn reflects his private signals. If mutual fund managers indeed suffer from the self-serving attribution bias, i.e., to increase the perceived precisions of their private signals too much after outperforming their benchmark indices and decrease their perceived precisions too little after underperforming, we expect a positive coefficient on SPR.

We include a host of control variables that are known to be related to mutual fund managers' portfolio choices in our full specification. For example, as suggested by the stylized model, we control for the aggregate benchmark-adjusted fund return ($sumret$) in quarters t-4 to t-1 to capture the updating rule when managers receive disconfirming public signals. We also control for the tracking error and turnover in the same period to reflect differences in managers' risk appetite and investment styles.[16] In addition, we construct a measure of total unrealized capital gains from a fund's inception to the end of quarter t-1 to rule out the effect of other behavioral biases, such as the disposition effect and "house money" effect.[17]

Other observable fund characteristics on the right hand side of the equation include investment flows and expense ratios in quarters t-4 to t-1, fund age and size dummies, and investment objective codes at the end of quarter t-1. All regression specifications also include year-fixed effects, and standard errors of all coefficient estimates are heteroskedasticity-consistent and clustered at both the year and fund levels.

[15]We find similar results with quarterly benchmark-adjusted fund returns. Our results are also robust to monthly SPR measures constructed in the previous quarter, six months, two years, or three years.

[16]Koijen (2010) finds that time-varying risk aversion could affect managers' Active Share.

[17]Thaler and Johnson (1990), in a series of experiments, find that agents with prior gains are more likely to accept gambles. In the context of mutual fund managers' portfolio choices, those with prior superior performance may be more risk-tolerant and thus have larger active positions.

4.2 The Effect of SPR on ΔAS

Table 2 presents the regression results. The dependent variable in Column 1 is ΔAS in quarter t. The coefficient on $SPR_{t-4:t-1}$ is both economically and statistically significant, with a point estimate of 0.06 (t=2.49). Put differently, a one-standard-deviation increase in SPR, *ceteris paribus*, leads to an increase of 0.55% in Active Share in the following quarter. To further examine the persistence in the effect of SPR on future ΔAS, in Columns 2 and 3, we replace ΔAS_t with ΔAS in quarters t+1 and t+2. The effect of SPR remains statistically significant in quarter t+1, and gradually dies off in (and after) quarter t+2. These results suggest that, after controlling for various observable fund characteristics (e.g., *sumret*), SPR has a persistent and significantly positive effect on subsequent changes in Active Share, consistent with the prediction of the stylized model.

Interestingly, the coefficient on aggregate benchmark-adjusted fund returns, $sumret_{t-4:t-1}$, which captures the updating of manager beliefs when their private signals are disconfirmed by public signals ($\underline{k}$ in (20)), is insignificant. This result suggests that managers do not decrease the perceived precisions of their private signals upon receiving disconfirming public signals, consistent with the notion that they blame bad luck or external factors for failures. One might be concerned about the correlation among SPR, *sumret*, and tracking error, because all of them are calculated using past fund returns. In unreported tests we run separate regressions by excluding one or two of these variables. In the absence of the other two variables, the coefficients on SPR, *sumret*, and tracking error are all positive (in three separate regressions), and the effect of SPR on Delta Active Share is the strongest, both in terms of economic and statistical significance. These results suggest that while the three variables are correlated, SPR has a significant residual impact even after we control for *sumret* and tracking error. We argue that this impact is evidence of mutual fund managers suffering from the self-serving attribution bias.

Among the control variables, the tracking error, turnover, and unrealized capital gain in the previous year have insignificant impact on changes in Active Share. Lagged investment flows have a significant and negative effect on ΔAS, likely due to a rebalancing motive: Upon receiving new investment, managers may initially invest the new capital in a few stocks and gradually diversify in subsequent periods, leading to lower Active Share.

4.3 Manager Experience

The results from the baseline regression analysis suggest that the average mutual fund manager suffers from the self-serving attribution bias. In this subsection, we provide further evidence for the biased attribution hypothesis by exploiting cross-sectional variation in managerial experience. Specifically, we predict that more experienced managers are less affected by the attribution bias for two reasons. First, experienced managers are more likely to appreciate and follow Bayesian updating rules. Second, these managers are also less uncertain about the precisions of their private signals, and are thus less likely to update their beliefs after observing an additional confirming or disconfirming public signal.

We construct two measures of experience: the number of years a manager has been in the mutual fund industry, and the number of years since a fund's inception.[18] The second measure is motivated by prior studies that use long-term fund returns as a measure of manager ability (e.g., Carhart (1997) and Cohen, Coval, and Pastor (2005)). At the end of each quarter, we sort all mutual funds into two halves based on either measure of manager experience. We then add the interaction term of the SPR measure with the experience dummy to our baseline regression specification.

The regression results, shown in Table 3 Panel A, are consistent with our prediction. When ranked by the number of years in the mutual fund industry (Column 1), the coefficient on SPR for managers in the bottom half is 0.05 (t=1.90), and that in the top half is 0.04 (t=1.55, not reported in the table). The difference between the two of -0.01 is statistically significant at the 5% level (t=-1.98). The results based on fund age are similar. The coefficient on SPR for funds in the bottom half is 0.07 (t=2.80), and that in the top half is 0.04 (t=1.16). The difference of -0.03 is again statistically significant at the 5% level (t=-2.00). These results suggest that inexperienced managers are more likely affected by behavioral biases, while the more experienced ones, having learned from their prior mistakes, are immune to these biases.

In a related vein, we examine differential effects of SPR for mutual funds managed by a single manager vs. a team of managers. One might expect that managers in a team-managed

[18]We track each manager's experience in the mutual fund industry by matching manager names across mutual funds reported in the CRSP database. We drop mutual funds with missing manager names from the analysis.

fund would be less vulnerable to the self-serving attribution bias, as they can perhaps keep each other in check.[19] To test this prediction, we add an interaction term of SPR with an indicator variable of team-managed funds to our baseline regression specification. The coefficient on the interaction term is negative but insignificant, providing some very weak evidence for this prediction.

4.4 SPR and Future Fund Performance

If managers suffer from the self-serving attribution bias, and thus make suboptimal portfolio decisions and/or trade excessively, we should see deteriorating future performance as managers get overconfident. To test this prediction, we conduct the following panel regression:

$$perf_{i,t+1:t+k} = \alpha + \beta_1 * SPR_{i,t-4:t-1} + \beta_2 * sumret_{i,t-4:t-1} + \gamma * CONTROL. \tag{25}$$

We employ a variety of measures of fund performance as the dependent variable: the average monthly fund returns in the next three, six, and twelve months, and their corresponding Sharpe ratios, as well as the Carhart four-factor monthly fund alpha in the subsequent one and three years and their associated information ratios.

The main independent variables in the regression include the sum of positive benchmark-adjusted monthly returns in quarters t-4 to t-1 ($SPR_{t-4:t-1}$), the aggregate benchmark-adjusted fund return in the same period ($sumret_{t-4:t-1}$), Active Share at the end of quarter t-1 (AS_{t-1}), and the change in Active Share in quarter t (ΔAS_t). If we think of quarter t as the event quarter, in which managers update their beliefs about the precisions of their private signals, we are then interested in knowing how pre-event SPR is related to post-event mutual fund performance. Our main prediction is that β_1 should be significantly negative.

We also include a list of control variables on the right hand side of the equation, such as the annual expense ratio and investment flows in the previous four quarters, and fund size, age, and objective codes at the end of quarter t-1. All regression specifications include year-fixed effects and standard errors of all coefficient estimates are clustered at both the year and fund levels.

[19] Alternatively, one could argue that managers in a team are more susceptible to behavioral biases due to herding and other group dynamics.

The results shown in Table 4 support the prediction that biased attribution negatively impacts future fund performance. In Panel A, we use the average monthly fund returns as the dependent variables. Specifically, we examine monthly fund returns (before fees and expenses) in the following three, six, and twelve months in Columns 1, 2, and 3, respectively. The coefficients on SPR are negative in all three regression specifications, but with marginal statistical significance. In Panel B, we repeat the analyses except that now we replace average monthly fund returns with the corresponding Sharpe ratios. The coefficients on SPR are -0.812 (t=-2.13), -0.621 (t=-2.77), and -0.426 (t=-2.95) for Sharpe ratios calculated in the following three, six, and twelve months, respectively. Put differently, a one-standard-deviation increase in SPR leads to a reduction in annualized Sharpe ratio by 13.38% in the subsequent year. The finding that SPR has a more significant impact on future Sharpe ratios than on average fund returns is consistent with the notion that overconfident managers tend to bare idiosyncratic risk without earning superior returns.

In Panels C and D of Table 4, we conduct the same analyses except that now we focus on risk-adjusted mutual fund performance. Since we need to estimate beta loadings on the Carhart four factors for each fund, we examine fund performance over an extended period, e.g., the subsequent 12 or 36 months. Specifically, we examine the Carhart four-factor fund alphas calculated from subsequent 12 and 36 monthly returns in Panel C, and the corresponding information ratios in Panel D, respectively. The results are consistent with those in Panels A and B. The coefficients on SPR are negative in three out of four regression specifications, and are statistically significant in the two measures that use 36 months. A one-standard-deviation increase in SPR leads to a reduction in annual abnormal fund returns by 78 basis points (t=-2.42) and a reduction in annualized information ratio by 9.96% (t=-3.09) in the following three years.

For the control variables, consistent with prior studies on mutual fund performance persistence (e.g., Carhart (1997)), we find *sumret* weakly and positively predicts subsequent fund performance, yet most of the predictability lies in the short run and is for total fund returns. Consistent with the findings in Wermers (2003), Frazzini and Lamont (2008), and Lou (2010), capital flows to mutual funds in the previous year significantly and negatively predict abnormal fund returns in the next one to three years.

In addition, as in Cremers and Petajisto (2009), we find that Active Share positively predicts future abnormal fund performance. Surprisingly, the predictive power comes exclusively from lagged Active Share, rather than the most recent changes in Active Share. In fact, in a number of regression specifications, ΔAS significantly and negatively predicts subsequent fund performance. Since we control for SPR in our regression, $\Delta ActiveShare$, in theory, only reflects information-driven trading. Therefore, if managers on average have stock picking ability, such ability should be more evident in changes of Active Share. There are two potential explanations for this puzzling finding. First, while Active Share is a general measure of manager ability, it is unclear how new information should affect Active Share; it may be the case that sometimes moving toward the benchmark is a wise decision. Second, this finding can be potentially consistent with the result in Huang, Sialm, and Zhang (2010) that managers with increasing risk-taking, which is likely related to Active Share, have lower subsequent returns on average.

4.5 SPR and Future Holdings-Based Performance

To further examine the extent to which the reduction in performance in relation to SPR is due to poor portfolio choices or excessive trading, we repeat the same analyses as in Table 4 using holdings-based fund returns.[20] Specifically, assuming that mutual funds do not update their positions between two consecutive reporting dates, we calculate a hypothetical series of fund returns based on these reported holdings. The results, shown in Table 5, are similar to those in Table 4.

As can be seen in Panel A, SPR negatively predicts the average monthly fund returns in the subsequent three, six, and twelve months, yet with marginal statistical significance. Its impact on subsequent Sharpe ratios (in Panel B) are all statistically significant. Specifically, a one-standard-deviation increase in SPR leads to a decrease in annualized Sharpe ratio by 11.81% (t=-2.73) in the subsequent year. Panels C and D report the effect of SPR on the subsequent Carhart four-factor fund alphas and information ratios. A one-standard-deviation increase in SPR leads to a reduction in annual abnormal fund returns by 57 basis points (t=-2.03) and a reduction in annualized information ratio by 7.71% (t=-2.36) in the

[20] As discussed in Kacperczyk, Sialm, and Zheng (2008), the difference between realized fund returns and hypothetical holdings-based returns reflects trading costs and the performance of unobserved intra-quarter fund trades.

following three years. These results imply that around three quarters of the underperformance resulting from biased attribution is driven by managers' poor portfolio choices, while the remaining quarter is due to trading costs and unobserved intra-quarter fund trades.

The negative link between SPR and future fund performance that we document in this section has two implications. First, it adds to the extensive literature that tries to identify managers with superior skills. But instead of identifying skills, we point out which managers investors should avoid. Specifically, investors should not only pay attention to past returns of a fund manager, but also his return path. If a manager experiences a large SPR, he is likely to get overconfident in his skills, which tends to lower his future performance. Moreover, the negative link between SPR and subsequent performance also completes the picture of investor overconfidence dynamics. An overconfident manager tends to experience sub-par returns relative to his peers, which in turn deflates his confidence. As a result, a typical fund manager does not get infinitely overconfident.

5 Across-Industry and Within-Industry Active Share

In this section we examine more closely the changes in fund managers' portfolios in response to SPR. In particular, we partition Active Share into two components: Across-Industry Active Share ($AIAS$), which measures a portfolio's deviation from its benchmark index in industry weights, and Within-Industry Active Share ($WIAS$), which measures the average deviation within a typical industry. This partition allows us to examine whether managers become more concentrated industry pickers or stock pickers when they increase their Active Share. $AIAS$ and $WIAS$ are defined as follows.[21]

$$AcrossIndustryActiveShare(AIAS) = \frac{1}{2}\sum_{i=1}^{I}|w_i^{mgr} - w_i^{benchmark}|, \tag{26}$$

[21] It is noted that $AIAS$ and $WIAS$ do not sum up exactly to the Active Share of a portfolio. Analyzing the two components separately, however, can still help us gain some insights into managers' overconfident behavior.

$$WithinIndustryActiveShare(WIAS) = \frac{1}{2}\sum_{i=1}^{I}(w_i^{mgr} * \sum_{n=1}^{N_i}|\frac{w_n^{mgr}}{w_i^{mgr}} - \frac{w_n^{benchmark}}{w_i^{benchmark}}|)$$
$$= \frac{1}{2}\sum_{i=1}^{I}\sum_{n=1}^{N_i}|w_n^{mgr} - \frac{w_i^{mgr}}{w_i^{benchmark}}w_n^{benchmark}|, \quad (27)$$

where N_i is the number of stocks in industry i and I is the total number of industries.[22] Note that there will be more across-industry variation in Active Share if the industry classification is more refined, but this comes at the cost of lower average variation in within-industry Active Share. In light of this tradeoff, we use the 48-industry classification in Fama and French (1997) in our analyses.[23] Our decision to dissect Active Share along the industry dimension is motivated by the finding in Kacperczyk, Sialm, and Zheng (2005) that industry concentration is an important predictor of future fund performance.[24] One interpretation of their results is that some managers have superior information in selecting stocks in specific industries, and therefore tilt their portfolio weights disproportionately to those industries. Alternatively, some managers may be good industry timers, who load more heavily on those industries with higher expected returns. Similarly, $WIAS$ may also be a strong predictor of future fund performance if some managers are good stock pickers in general.

We calculate $\Delta AIAS$ and $\Delta WIAS$ in a way similar to ΔAS (Delta Active Share) – i.e., to only focus the part of changes that is due to active trading. We then re-estimate regression specification (24) except that we replace ΔAS with $\Delta AIAS$ or $\Delta WIAS$. Table 6 presents the regression results. Given a high SPR, managers increase their Within-Industry Active Share and yet keep their Across-Industry Active Share almost unchanged. A one-standard-deviation increase in SPR leads to an increase in $WIAS$ of 0.86% (t=2.88) or 1.19% of the average $WIAS$ in our sample, and an increase in $AIAS$ of only 0.04% (t=0.09). One potential interpretation is that managers get more confident in their overall stock-picking ability and thus become more active stock pickers in general in response to SPR.

[22] If the manager has zero weight in industry i ($w_i^{mgr} = 0$), then this industry will not contribute to his $WIAS$. If the benchmark has zero weight in industry i ($w_i^{benchmark} = 0$), then we treat $\frac{w_n^{benchmark}}{w_i^{benchmark}}$ as 0 for all stocks in the industry.

[23] Cremers and Petajisto (2009) construct a similar industry-level Active Share measure and observe that it only weakly predicts future fund performance. However, they use a 10-industry classification in their definition of the across-industry Active Share measure, which likely explains the differences between their and our findings.

[24] The industry concentration measure is different from the across-industry Active Share measure in that the former sums up squared differences, while the latter sums up absolute deviations.

We then ask the question whether $AIAS$, $WIAS$, or both can predict future fund performance. We conduct similar analyses to those reported in Panels C and D of Table 4 (equation (25)), expect that we replace Active Share and Delta Active Share with their across-industry and within-industry counterparts. The results are shown in Table 7. Consistent with Kacperczyk, Sialm, and Zheng (2005), lagged Across-Industry Active Share significantly and positively predicts future fund performance. A one-standard-deviation increase in $AIAS$ leads to increases in annual Carhart four-factor alpha of 74 (t=3.59) and 65 basis points (t=3.59) in the following one and three years, respectively. Similarly, a one-standard-deviation increase in the measure is also associated with increases in annualized information ratio of 5.97% (t=1.93) and 8.21% (t=2.87) in the following one and three years. In contrast, lagged Within-Industry Active Share has much weaker predictive power for future fund performance, either measured by the Carhart four-factor alpha or the information ratio.

Taken together, the evidence suggests that one source of activeness ($AIAS$) has strong performance implications while the other ($WIAS$) does not. However, in response to a high SPR, mutual fund managers significantly increase the "bad" Active Share by becoming more active stock pickers in all industries.

Given that managers increase their $WIAS$ in response to SPR, a further question is whether they tend to be more active stock pickers in industries that they are more familiar with or less familiar with. Answering this question can help shed light on why SPR is negatively related to subsequent fund performance. We measure a manager's familiarity with each industry using his portfolio weight in the industry relative to hsi benchmark index. This is motivated by the finding that $AIAS$ (or industry concentration) significantly and positively predicts future performance, which implies that industries with large abnormal weights tend to be those in which managers have information advantages. Our test statistic for the aforementioned question is thus the correlation between benchmark-adjusted industry weights and within-industry deviations:

$$Corr(IndWght, Deviation) = corr(w_i^{mgr} - w_i^{benchmark}, \sum_{n=1}^{N_i} |\frac{w_n^{mgr}}{w_i^{mgr}} - \frac{w_n^{benchmark}}{w_i^{benchmark}}|), \qquad (28)$$

where $IndWght$ represents the portfolio weight in each industry compared to the benchmark, and $Deviation$ is the summand in the $WIAS$ calculation. An increase in this correlation implies that managers become more active stock pickers in industries they are more familiar with, and a decrease indicates otherwise.

Table 8 shows the results of the regression of $Corr(IndWght, Deviation)$ on lagged SPR and other control variables. The effect of lagged SPR on the correlation measure is significantly negative after controlling for the lagged correlation. Specifically, a one-standard-deviation increase in SPR leads to a decrease in unexpected $Corr(IndWght, Deviation)$ by 1.40% (t=-3.42). Together with the result in Table 6 that managers do not substantially alter industry weights as they get overconfident, the negative impact of lagged SPR on the correlation suggests that managers pick stocks more actively in industries where they do not have skills. A plausible interpretation of our results is that mutual fund managers, who are good at selecting stocks in a few industries, become overconfident in their private signals about all stocks after achieving a high SPR, and subsequently earn lower abnormal returns due to sub-optimal portfolio choices.

6 Robustness Checks

6.1 Other Measures of Overconfidence

We test the robustness of our results to alternative measures of managerial confidence. Prior literature suggests turnover as one such variable (e.g., Barber and Odean (2000, 2001, 2002)). As discussed in Section 3 as a possible extension to our stylized model, if managers get overconfident not only about their existing signals, but also about their information sources or their ways of collecting and processing information after observing a high SPR, biased attribution can affect subsequent trading frequencies.

To test this prediction, we repeat our regression analysis based on equation (24), but instead we use changes in aggregate turnover in the following year as the dependent variable.[25] The results, shown in Table 9, are consistent with our prediction that SPR is significantly and

[25] We calculate quarterly fund turnover from Thomson mutual fund holdings as the sum of quarterly purchases and sales scaled by total positions at the end of the quarter. We then sum up the turnover over four consecutive quarters to derive annual turnover. The change in annual turnover is the turnover from quarter t to $t+3$ minus the turnover from quarter $t-4$ to $t-1$.

positively related to managers' trading volume subsequently. Specifically, a one-standard-deviation increase in SPR, *ceteris paribus*, leads to an increase in annual turnover by 13.09% (t=3.20).[26] For reference, the average annual fund turnover in our sample is about 150%. Overall, our results suggest that SPR, which reflects managers' differential responses to confirming and disconfirming public signals, is strongly and positively related to mutual fund managers' confidence, as measured by both Active Share and fund turnover.

6.2 Other Ways to Calculate SPR

For most part of our empirical analyses, we use the sum of positive benchmark-adjusted fund returns as a proxy for n^+ and the absolute sum of negative benchmark-adjusted fund returns as a proxy for n^- (n^+ and n^- are formally introduced in Proposition (1)). We use either monthly or quarter fund returns as separate signals about manager ability. We also construct SPR using past benchmark-adjusted fund returns from various horizons, such as six months, one year, and three years. The results are similar.

For further robustness checks, we define two sets of alternative measures of SPR. The first set uses the number of months with positive and negative benchmark-adjusted returns as proxies for n^+ and n^-, respectively. In the second set, we put larger weights on more recent months. When summing up the outperformance and underperformance in the previous twelve months, we assign a weight that is monotonically decreasing with the distance between the month in question and the month in which the benchmark-adjusted return is measured (e.g., the closest month receives a weight of 12/78, the month before 11/78, and the most distant month 1/78, etc.). Our main conclusion remains unchanged.[27]

6.3 The Flow-SPR Relation

Given that SPR is negatively associated with subsequent fund performance in terms of both abnormal fund returns and the information ratio, an immediate question is whether investors respond to SPR optimally. We gauge investor reactions by examining capital

[26] In a related study, Putz and Ruenzi (2010) find that mutual fund managers trade more after good performance. However, this is not necessarily a violation of Bayesian updating.

[27] For brevity, the results are untabulated.

flows to mutual funds. We conduct a regression analysis based on (24), but instead we use percentage investment flows in the subsequent quarter as the dependent variable. As shown in Table 10, investors respond only mildly to past SPR. The coefficient on SPR in the regression is -0.16 with a t-statistic of -1.47, indicating that retail investors are not fully aware of the adverse impact of biased attribution on managers' subsequent performance.

In a related vein, we conduct an additional (untabulated) test of manager behavior at calendar year-ends vs. other quarter-ends. If our results are, to some extent, driven by managers' incentives to cater to fund investors, who themselves get overconfident about their fund selecting ability after experiencing a high SPR, we would expect to observe a difference in manager behavior between the first quarter of a year (while SPR is measured over the past calendar year) and other quarters. This is because investors likely pay more attention to calendar-year performance (e.g., Chevalier and Ellison (1997)). However, when we add an extra interaction term of SPR and a dummy variable indicating a full calendar year to our baseline regression, the coefficient on the interaction term is not statistically significant, suggesting that the relationship between Delta Active Share and SPR is not different across quarters.

7 Conclusion

This paper is one of the first empirical attempts to analyze the dynamics of investor overconfidence. Using Active Share as our main measure, we find that mutual fund managers accumulate unwarranted confidence as they take too much credit for successes and too little blame for failures. We also document that manager overconfidence is associated with future underperformance, both in terms of abnormal fund returns and the information ratio. In addition, the underperformance is largely driven by managers' poor portfolio choices, particularly, by their decisions to place more active bets in industries that they are unfamiliar with. Taken together, the evidence presented in this paper suggests that even sophisticated investors like active mutual fund managers are susceptible to behavioral biases.

Our paper also sheds new light on the determinants of Active Share. Prior literature identifies managerial ability and risk aversion as two main determinants of Active Share and documents a strong positive relation between Active Share and future fund performance.

Our results suggest a third determinant of Active Share – manager overconfidence, which is negatively related to future fund performance. Specifically, overconfident managers attach too high precisions to their private signals, hence deviate too much from their benchmark indices than they should otherwise, and consequently underperform. Future research on Active Share should carefully disentangle these three components to better reflect managerial ability.

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Table 1
Descriptive Statistics of Active Share, Fund Returns and Characteristics

This table presents the summary statistics for our sample of actively managed mutual funds. *Active Share* is calculated as one half of the sum of absolute deviations in portfolio weights of an active portfolio from its benchmark index. *Delta Active Share* is the log *Active Share* of the reported portfolio minus the log *Active Share* of a hypothetical portfolio had the manager not traded in the quarter. *Across-Industry Active Share* (*AIAS*) and *Within-Industry Active Share* (*WIAS*) are similar to *Active Share*, calculated using the deviation from the benchmark's industry weights and the average deviation within a typical industry, respectively. *Delta AIAS* and *Delta WIAS* are similar to *Delta Active Share.*

Sum of Positive Returns (*SPR*) is the sum of positive monthly benchmark-adjusted returns in the past 12 months. *Sumret* is the sum of monthly benchmark-adjusted returns in the past 12 months. *Tracking Error* (*12-month*) is the standard deviation of the benchmark-adjusted returns in the past 12 months. *Flow* is the annual flow divided by the total net assets. *Unrealized Gains* are the cumulative unrealized gains divided by total purchase value. *Turnover* is the annual sum of all purchases and sales divided by the value of total holdings. *Expenses* is the annual expense ratio. *Fund Age* is the number of years since fund inception. *Size* is the total net assets of the fund.

The following performance measures are calculated based on pre-expense returns from CRSP: *Average Fund Returns* are the monthly average returns; *Sharpe Ratio* is the average monthly excess returns divided by the standard deviation of returns; *Realized Alpha* is the alpha calculated based on the regression of monthly excess returns on the monthly four factors; *Realized Information Ratio* is the ratio of *Realized Alpha* to the standard deviation of regression residuals. *Corr* (*Ind Wght*, *Deviation*) is the correlation between benchmark-adjusted industry weights and within-industry deviations from the benchmark.

N = 46,510	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
Active Share (%)	78.528	16.590	69.253	82.487	91.419
Delta Active Share (%)	-0.665	7.954	-1.546	-0.095	0.961
Across-Industry Active Share (AIAS) (%)	36.491	14.346	26.516	35.010	45.045
Delta AIAS (%)	-1.432	13.400	-6.437	-0.632	4.327
Within-Industry Active Share (WIAS) (%)	71.630	16.899	60.786	73.654	85.268
Delta WIAS (%)	-0.542	9.757	-2.105	-0.051	1.826
Sum of Positive Returns (SPR) (%)	9.831	9.071	4.192	7.267	12.410
Sumret (%)	0.478	10.129	-4.037	-0.039	4.231
Tracking Error (12-month) (%)	1.969	1.636	1.050	1.603	2.430
Flow (%)	11.086	63.256	-13.607	-1.743	18.330
Unrealized Gains (%)	14.664	24.089	3.306	13.726	24.671
Turnover (%)	148.592	97.396	78.934	129.185	197.387
Expenses (%)	1.277	0.571	0.963	1.220	1.531
Fund Age	14.055	13.999	5.000	9.000	17.000
Size ($ billion)	1.027	3.623	0.062	0.205	0.677
Average 3-month Fund Return (%)	0.942	3.490	-0.581	1.164	2.789
Average 6-month Fund Return (%)	0.947	2.320	-0.034	1.138	2.149
Average 12-month Fund Return (%)	0.953	1.674	0.293	1.099	1.880
3-month Sharpe Ratio (%)	41.809	190.701	-25.413	25.477	83.708
6-month Sharpe Ratio (%)	24.542	54.298	-8.723	23.585	52.795
12-month Sharpe Ratio (%)	21.072	34.127	-0.244	21.509	42.701
Realized Alpha (12-month) (%)	0.048	0.877	-0.330	0.022	0.403
Realized Alpha (36-month) (%)	0.019	0.490	-0.190	0.015	0.228
Realized Information Ratio (12-month) (%)	-4.971	56.407	-29.526	105.959	268.068
Realized Information Ratio (36-month) (%)	0.741	25.726	-16.438	1.275	17.559
Corr(Ind Wght, Deviation) (%)	8.865	29.256	-10.918	9.704	28.796

Table 2

Regression of Delta Active Share on SPR

The table reports the regression of *Delta Active Share* on *SPR* (Sum of Positive Returns), the sum of benchmark-adjusted returns, and other fund characteristics. *Delta Active Share* is the log *Active Share* of the reported portfolio minus the log *Active Share* of a hypothetical portfolio had the manager not traded in the quarter. *Active Share* is calculated as one half of the sum of absolute deviations in portfolio weights of an active portfolio from its benchmark index.

SPR is the sum of positive monthly benchmark-adjusted returns in the past 12 months. *Sumret* is the sum of monthly benchmark-adjusted returns in the past 12 months. *Tracking Error* (12-*month*) is the standard deviation of the benchmark-adjusted returns in the past 12 months. *Flow* is the annual flow divided by the total net assets. *Unrealized Gains* are the cumulative unrealized gains divided by total purchase value. *Turnover* is the annual sum of all purchases and sales divided by the value of total holdings. *Expenses* is the annual expense ratio. *Investment Obj Code* 2 - 4 are investment objective code dummies (2 = aggressive growth, 3 = growth, 4 = growth and income). *Fund Age* $Q1$ - $Q4$ and *Size* $Q1$ - $Q4$ are, respectively, the age and total net asset quartile dummies (1 = youngest or largest). The subscript t represents quarter t and the timing of the variables (e.g., *Delta Active Share*$_{t\text{-}1:t}$ is calculated from quarter t-1 to t). Intercepts and estimates on the year dummies are not reported.

Heteroskedasticity-consistent time- and fund-clustered t-statistics are in parentheses. *, ** and *** denote 10%, 5% and 1% significance, respectively.

All coefficients are x 100	Delta Active Share$_{t-1:t}$ (%)	t-stat	Delta Active Share$_{t:t+1}$ (%)	t-stat	Delta Active Share$_{t+1:t+2}$ (%)	t-stat
SPR$_{t-4:t-1}$ (%)	6.100**	(2.49)	4.620**	(2.01)	1.745	(0.53)
Sumret$_{t-4:t-1}$ (%)	-1.340	(-1.21)	-1.343	(-0.98)	-0.830	(-0.44)
Tracking Error (12-month)$_{t-4:t-1}$ (%)	1.789	(0.26)	1.700	(0.22)	10.003	(0.58)
Flow$_{t-4:t-1}$ (%)	-0.698*	(-1.72)	-0.380***	(-2.59)	-0.122	(-1.17)
Unrealized Gains$_{t-1}$ (%)	0.181	(0.59)	0.117	(0.64)	0.080	(0.46)
Turnover$_{t-4:t-1}$ (%)	-0.112	(-0.93)	0.031	(0.51)	0.063	(1.36)
Expenses$_{t-4:t-1}$ (%)	52.396***	(3.16)	51.106***	(2.65)	47.798***	(2.63)
Investment Obj Code 2 (Agg. Growth)	29.059	(1.16)	37.827*	(1.58)	30.953	(1.38)
Investment Obj Code 3 (Growth)	53.679**	(2.47)	60.129***	(3.03)	51.971**	(2.30)
Investment Obj Code 4 (Growth & Income)	51.243*	(1.90)	61.020**	(2.23)	50.527*	(1.85)
Fund Age Q1 (Youngest)	-33.599	(-1.04)	-27.044	(-1.11)	-25.293	(-1.30)
Fund Age Q2	-23.215	(-0.72)	-15.616	(-0.59)	-16.429	(-0.80)
Fund Age Q3	-29.332	(-0.92)	-13.667	(-0.58)	-14.171	(-0.90)
Fund Age Q4 (Oldest)	-5.816	(-0.23)	6.455	(0.28)	9.872	(0.64)
Size Q1 (Largest)	13.688	(0.22)	4.195	(0.07)	-30.769	(-0.79)
Size Q2	26.746	(0.40)	2.713	(0.05)	-33.105	(-0.90)
Size Q3	21.787	(0.32)	5.593	(0.10)	-26.606	(-0.72)
Size Q4 (Smallest)	29.312	(0.43)	22.097	(0.40)	-12.258	(-0.34)
N	46510		44130		41846	
R Sq.	2.19%		1.96%		1.80%	

Table 3

Regression of Delta Active Share on SPR: Experienced Managers and Team-Managed Funds

The table reports the regression of *Delta Active Share* on *SPR* (Sum of Positive Returns), the sum of benchmark-adjusted returns, and other fund characteristics. Panel A includes an interaction term of *SPR* with experience proxies, and Panel B includes an interaction term of *SPR* with *Team Dummy*. The experience proxies are *Managers' Experience Dummy* and *Fund Age Dummy*. *Managers' Experience Dummy* indicates that the manager has above-median experience in the mutual fund industry. *Fund Age Dummy* indicates that the fund age (number of years since inception) is above the median. *Team Dummy* indicates that the fund is managed by a team. *Delta Active Share* is the log *Active Share* of the reported portfolio minus the log *Active Share* of a hypothetical portfolio had the manager not traded in the quarter. *Active Share* is calculated as one half of the sum of absolute deviations in portfolio weights of an active portfolio from its benchmark index.

SPR is the sum of positive monthly benchmark-adjusted returns in the past 12 months. *Sumret* is the sum of monthly benchmark-adjusted returns in the past 12 months. *Tracking Error* (12-*month*) is the standard deviation of the benchmark-adjusted returns in the past 12 months. *Flow* is the annual flow divided by the total net assets. *Unrealized Gains* are the cumulative unrealized gains divided by total purchase value. *Turnover* is the annual sum of all purchases and sales divided by the value of total holdings. *Expenses* is the annual expense ratio. *Investment Obj Code* 2 - 4 are investment objective code dummies (2 = aggressive growth, 3 = growth, 4 = growth and income). *Fund Age* $Q1$ - $Q4$ are the age (number of years since inception) quartile dummies (1 = youngest). *Size* $Q1$ - $Q4$ are the total net asset quartile dummies (1 = largest). The subscript t represents quarter t and the timing of the variables (e.g., *Delta Active Share*$_{t-1:t}$ is calculated from quarter t-1 to t). Intercepts and estimates on the year dummies are not reported.

Heteroskedasticity-consistent time- and fund-clustered t-statistics are in parentheses. *, ** and *** denote 10%, 5% and 1% significance, respectively.

Panel A: Experience Proxies	Managers' Experience		Fund Age	
All coefficients are x 100	Delta Active Share$_{t-1:t}$ (%)	t-stat	Delta Active Share$_{t-1:t}$ (%)	t-stat
SPR$_{t-4:t-1}$ (%)	4.918*	(1.90)	7.274***	(2.80)
SPR$_{t-4:t-1}$ (%) * Experience Proxy (Top Half)	-0.835**	(-1.98)	-3.325**	(-2.00)
Sumret$_{t-4:t-1}$ (%)	-0.478	(-0.37)	-1.303	(-1.15)
Tracking Error (12-month)$_{t-4:t-1}$ (%)	4.677	(0.63)	2.329	(0.31)
Flow$_{t-4:t-1}$ (%)	-0.573	(-1.58)	-0.704*	(-1.73)
Unrealized Gains$_{t-1}$ (%)	0.343	(1.07)	0.181	(0.60)
Turnover$_{t-4:t-1}$ (%)	-0.089	(-0.69)	-0.121	(-0.98)
Expenses$_{t-4:t-1}$ (%)	75.981***	(3.03)	52.338***	(3.18)
Investment Obj Code 2 (Agg. Growth)	0.380	(1.23)	0.290	(1.16)
Investment Obj Code 3 (Growth)	0.520*	(1.77)	0.496**	(2.41)
Investment Obj Code 4 (Growth & Income)	0.511	(1.36)	0.457*	(1.75)
Fund Age Q1 (Youngest)	-0.731**	(-2.17)	-0.360	(-1.14)
Fund Age Q2	-0.435	(-1.58)	-0.234	(-0.73)
Fund Age Q3	-0.365*	(-1.75)	0.026	(0.06)
Fund Age Q4 (Oldest)	-0.179	(-0.96)	0.268	(0.82)
Size Q1 (Largest)	-0.460	(-0.56)	0.139	(0.22)
Size Q2	-0.454	(-0.58)	0.277	(0.41)
Size Q3	-0.463	(-0.56)	0.231	(0.33)
Size Q4 (Smallest)	-0.343	(-0.41)	0.308	(0.44)
N	32745		46510	
R Sq.	2.08%		2.22%	

Table 3 (cont'd)

Panel B: Team-Managed and Individual-Managed Funds		
All coefficients are x 100	Delta Active Share$_{t-1:t}$ (%)	t-stat
SPR$_{t-4:t-1}$ (%)	7.053**	(2.42)
SPR$_{t-4:t-1}$ (%) * Team Dummy	-1.495	(-1.05)
Sumret$_{t-4:t-1}$ (%)	-1.408	(-1.12)
Tracking Error (12-month) $_{t-4:t-1}$ (%)	2.210	(0.28)
Flow$_{t-4:t-1}$ (%)	-0.724*	(-1.68)
Unrealized Gains $_{t-1}$ (%)	0.202	(0.62)
Turnover$_{t-4:t-1}$ (%)	-0.135	(-0.98)
Expenses$_{t-4:t-1}$ (%)	70.125***	(3.05)
Team Dummy	0.404	(1.57)
Investment Obj Code 2 (Agg. Growth)	0.295	(1.11)
Investment Obj Code 3 (Growth)	0.515**	(2.36)
Investment Obj Code 4 (Growth & Income)	0.456	(1.58)
Fund Age Q1 (Youngest)	-0.467	(-1.25)
Fund Age Q2	-0.237	(-0.65)
Fund Age Q3	-0.311	(-0.87)
Fund Age Q4 (Oldest)	-0.062	(-0.22)
Size Q1 (Largest)	0.319	(0.30)
Size Q2	0.420	(0.39)
Size Q3	0.413	(0.37)
Size Q4 (Smallest)	0.497	(0.45)
N	36576	
R Sq.	2.33%	

Table 4
Regression of Future Realized Performance Measures on SPR and Active Share

This table shows the results of the regression of future fund performance measures on *SPR* and *Active Share*. All performance measures are calculated based on pre-expense returns from CRSP. The measures are 3-*month*, 6-*month*, and 12-*month Fund Return* in Panel A, *Sharpe Ratio* (3-*month*), *Sharpe Ratio* (6-*month*), *Sharpe Ratio* (12-*month*) in Panel B, Realized Alpha (12-month) and Realized Alpha (36-month) *in* Panel C, and *Realized Information Ratio* (12-*month*) and *Realized Information Ratio* (36-*month*) in Panel D. 3-*month*, 6-*month*, and 12-*month Fund Return* are, respectively, the monthly average 3-month, 6-month, and 12-month returns. *Sharpe Ratio* is the average monthly excess returns divided by the standard deviation of returns. *Realized Alpha* is the alpha calculated based on the regression of monthly excess returns on the monthly four factors. *Realized Information Ratio* is the ratio of *Realized Alpha* to the standard deviation of regression residuals.

SPR is the sum of positive monthly benchmark-adjusted returns in the past 12 months. *Active Share* is calculated as one half of the sum of absolute deviations in portfolio weights of an active portfolio from its benchmark index. *Delta Active Share* is the log *Active Share* of the reported portfolio minus the log *Active Share* of a hypothetical portfolio had the manager not traded in the quarter. *Sumret* is the sum of monthly benchmark-adjusted returns in the past 12 months. *Flow* is the annual flow divided by the total net assets. *Expenses* is the annual expense ratio. *Size* is the total net assets of the fund. *Investment Obj Code* 2 - 4 are investment objective code dummies (2 = aggressive growth, 3 = growth, 4 = growth and income). *Fund Age* $Q1$ - $Q4$ are the age quartile dummies (1 = youngest). The subscript t represents quarter t and the timing of the variables (e.g., 3-*month Fund Return* $_{t:t+1}$ is calculated from quarter t to t+1). Intercepts and estimates on the year dummies are not reported.

Heteroskedasticity-consistent time- and fund-clustered t-statistics are in parentheses. *, ** and *** denote 10%, 5% and 1% significance, respectively.

Panel A: Average Monthly Fund Realized Returns						
All coefficients are x 100	3-month Fund Return$_{t:t+1}$ (%)	t-stat	6-month Fund Return$_{t:t+2}$ (%)	t-stat	12-month Fund Return$_{t:t+4}$ (%)	t-stat
SPR$_{t-4:t-1}$ (%)	-3.775	(-1.55)	-3.117*	(-1.65)	-2.255**	(-2.14)
Active Share$_{t-1}$ (%)	1.238	(1.52)	1.132	(1.58)	1.134**	(2.03)
Delta Active Share$_{t-1:t}$ (%)	-0.174	(-0.51)	-0.484**	(-2.44)	-0.347*	(-1.92)
Sumret$_{t-4:t-1}$ (%)	2.272**	(2.50)	1.573*	(1.80)	0.859	(1.15)
Flow$_{t-4:t-1}$ (%)	-0.055	(-1.19)	-0.066	(-1.56)	-0.080*	(-1.83)
Expenses$_{t-4:t-1}$ (%)	-7.075	(-1.50)	-2.770	(-0.60)	-2.268	(-0.55)
Log Size$_{t-1}$	-0.847**	(-2.15)	-0.794**	(-2.38)	-0.565**	(-2.12)
Investment Obj Code 2 (Agg. Growth)	0.081	(0.51)	0.017	(0.11)	0.061	(0.48)
Investment Obj Code 3 (Growth)	0.037	(0.35)	-0.012	(-0.12)	0.022	(0.26)
Investment Obj Code 4 (Growth & Income)	-0.038	(-0.32)	-0.046	(-0.38)	-0.010	(-0.10)
Fund Age Q1 (Youngest)	-0.057	(-0.64)	-0.021	(-0.21)	0.025	(0.34)
Fund Age Q2	-0.109	(-1.26)	-0.027	(-0.38)	-0.045	(-1.05)
Fund Age Q3	-0.132	(-1.23)	-0.068	(-0.84)	-0.094*	(-1.75)
Fund Age Q4 (Oldest)	-0.103	(-1.07)	-0.009	(-0.16)	-0.045	(-1.07)
N	46313		44460		40804	
R Sq.	23.72%		34.58%		50.55%	

Table 4 (cont'd)

Panel B: Sharpe Ratios						
All coefficients are x 100	3-month Sharpe $\text{Ratio}_{t:t+1}$ (%)	t-stat	6-month Sharpe $\text{Ratio}_{t:t+2}$ (%)	t-stat	12-month Sharpe $\text{Ratio}_{t:t+4}$ (%)	t-stat
$\text{SPR}_{t-4:t-1}$ (%)	-81.197**	(-2.13)	-62.065***	(-2.77)	-42.558***	(-2.95)
Active Share_{t-1} (%)	10.788	(0.32)	14.552	(1.05)	14.630*	(1.71)
Delta Active $\text{Share}_{t-1:t}$ (%)	-12.442	(-0.99)	-9.026**	(-2.38)	-4.462	(-1.29)
$\text{Sumret}_{t-4:t-1}$ (%)	98.095***	(2.94)	41.848**	(2.36)	26.460**	(2.26)
$\text{Flow}_{t-4:t-1}$ (%)	-2.459	(-1.46)	-0.997	(-1.57)	-0.898	(-1.50)
$\text{Expenses}_{t-4:t-1}$ (%)	-175.393	(-0.95)	-167.980	(-1.61)	-113.622	(-1.49)
Log Size_{t-1}	-8.380	(-0.45)	-10.879*	(-1.73)	-8.980*	(-1.89)
Investment Obj Code 2 (Agg. Growth)	-3.485	(-0.53)	-5.746*	(-1.92)	-2.696	(-1.43)
Investment Obj Code 3 (Growth)	2.195	(0.51)	-0.280	(-0.12)	0.699	(0.47)
Investment Obj Code 4 (Growth & Income)	2.515	(0.31)	3.529	(0.87)	2.773	(1.20)
Fund Age Q1 (Youngest)	-0.755	(-0.15)	-0.733	(-0.29)	-0.210	(-0.13)
Fund Age Q2	-1.027	(-0.21)	-2.028	(-1.03)	-1.947*	(-1.69)
Fund Age Q3	-4.373	(-0.74)	-1.733	(-0.70)	-2.319*	(-1.76)
Fund Age Q4 (Oldest)	-2.632	(-0.55)	-0.130	(-0.06)	-0.818	(-0.70)
N	46313		44460		40804	
R Sq.	11.37%		40.14%		57.79%	

Panel C: Alphas				
All coefficients are x 100	Realized Alpha (12-month) $_{t:t+4}$ (%)	t-stat	Realized Alpha (36-month) $_{t:t+12}$ (%)	t-stat
$\text{SPR}_{t-4:t-1}$ (%)	-0.547	(-1.51)	-0.714**	(-2.42)
Active Share_{t-1} (%)	0.215	(1.29)	0.248***	(2.74)
Delta Active $\text{Share}_{t-1:t}$ (%)	-0.023	(-0.34)	-0.028	(-0.70)
$\text{Sumret}_{t-4:t-1}$ (%)	0.501*	(1.80)	0.249	(0.88)
$\text{Flow}_{t-4:t-1}$ (%)	-0.047**	(-2.22)	-0.030***	(-2.66)
$\text{Expenses}_{t-4:t-1}$ (%)	0.352	(0.21)	-0.033	(-0.02)
Log Size_{t-1}	-0.206	(-1.24)	-0.193	(-1.19)
Investment Obj Code 2 (Agg. Growth)	0.017	(0.31)	0.005	(0.13)
Investment Obj Code 3 (Growth)	0.009	(0.28)	0.005	(0.18)
Investment Obj Code 4 (Growth & Income)	0.004	(0.11)	-0.009	(-0.31)
Fund Age Q1 (Youngest)	0.069	(1.48)	0.018	(0.53)
Fund Age Q2	0.013	(0.41)	-0.043	(-1.52)
Fund Age Q3	-0.019	(-0.72)	-0.032*	(-1.66)
Fund Age Q4 (Oldest)	-0.004	(-0.14)	-0.042*	(-1.76)
N	39457		33305	
R Sq.	9.70%		8.45%	

Table 4 (cont'd)

Panel D: Information Ratios				
All coefficients are x 100	Realized Information Ratio (12-month) $_{t:t+4}$ (%)	t-stat	Realized Information Ratio (36-month) $_{t:t+12}$ (%)	t-stat
$SPR_{t-4:t-1}$ (%)	5.643	(0.27)	-31.686***	(-3.09)
Active Share $_{t-1}$ (%)	4.252	(0.69)	19.575***	(3.13)
Delta Active Share $_{t-1:t}$ (%)	-8.923	(-1.15)	0.201	(0.06)
$Sumret_{t-4:t-1}$ (%)	-4.250	(-0.40)	14.715	(1.24)
$Flow_{t-4:t-1}$ (%)	-2.081**	(-2.46)	-1.143**	(-2.40)
$Expenses_{t-4:t-1}$ (%)	-58.320	(-0.61)	-76.253	(-0.90)
Log $Size_{t-1}$	-14.789**	(-2.56)	-7.887	(-0.93)
Investment Obj Code 2 (Agg. Growth)	3.413	(1.47)	-1.474	(-0.60)
Investment Obj Code 3 (Growth)	1.770	(1.18)	-1.061	(-0.63)
Investment Obj Code 4 (Growth & Income)	-0.826	(-0.34)	-2.437	(-1.31)
Fund Age Q1 (Youngest)	1.587	(0.63)	-0.125	(-0.06)
Fund Age Q2	-0.773	(-0.34)	-2.195	(-1.17)
Fund Age Q3	-1.729	(-1.25)	-1.261	(-0.83)
Fund Age Q4 (Oldest)	-1.795	(-0.89)	-2.726	(-1.64)
N	39457		33305	
R Sq.	4.21%		10.41%	

Table 5
Regression of Future Holdings Performance Measures on SPR and Active Share

This table shows the results of the regression of future fund performance measures on *SPR* and *Active Share*. All performance measures are calculated based on gross returns on the funds stock holdings. The measures are 3-*month*, 6-*month*, and 12-*month Fund Return* in Panel A, *Sharpe Ratio* (3-*month*), *Sharpe Ratio* (6-*month*), *Sharpe Ratio* (12-*month*) in Panel B, Holdings Alpha (12-month) and Holdings Alpha (36-month) *in* Panel C, and *Holdings Information Ratio* (12-*month*) and *Holdings Information Ratio* (36-*month*) in Panel D. 3-*month*, 6-*month*, and 12-*month Holdings Return* are, respectively, the monthly average 3-month, 6-month, and 12-month returns. *Sharpe Ratio* is the average monthly excess returns divided by the standard deviation of returns. *Holdings Alpha* is the alpha calculated based on the regression of monthly excess returns on the monthly four factors. *Holdings Information Ratio* is the ratio of *Realized Alpha* to the standard deviation of regression residuals.

SPR is the sum of positive monthly benchmark-adjusted returns in the past 12 months. *Active Share* is calculated as one half of the sum of absolute deviations in portfolio weights of an active portfolio from its benchmark index. *Delta Active Share* is the log *Active Share* of the reported portfolio minus the log *Active Share* of a hypothetical portfolio had the manager not traded in the quarter. *Sumret* is the sum of monthly benchmark-adjusted returns in the past 12 months. *Flow* is the annual flow divided by the total net assets. *Expenses* is the annual expense ratio. *Size* is the total net assets of the fund. *Investment Obj Code* 2 - 4 are investment objective code dummies (2 = aggressive growth, 3 = growth, 4 = growth and income). *Fund Age* $Q1$ - $Q4$ are the age quartile dummies (1 = youngest). The subscript t represents quarter t and the timing of the variables (e.g., 3-*month Fund Return* $_{t:t+1}$ is calculated from quarter t to $t+1$). Intercepts and estimates on the year dummies are not reported.

Heteroskedasticity-consistent time- and fund-clustered t-statistics are in parentheses. *, ** and *** denote 10%, 5% and 1% significance, respectively.

Panel A: Average Monthly Fund Holdings Returns						
All coefficients are x 100	3-month Holdings Return$_{t:t+1}$ (%)	t-stat	6-month Holdings Return$_{t:t+2}$ (%)	t-stat	12-month Holdings Return$_{t:t+4}$ (%)	t-stat
SPR$_{t-4:t-1}$ (%)	-4.072	(-1.56)	-3.376*	(-1.72)	-2.338**	(-2.21)
Active Share$_{t-1}$ (%)	1.312	(1.55)	1.193	(1.63)	1.166**	(2.14)
Delta Active Share$_{t-1:t}$ (%)	-0.095	(-0.26)	-0.458**	(-2.04)	-0.325*	(-1.75)
Sumret$_{t-4:t-1}$ (%)	2.305**	(2.34)	1.535*	(1.65)	0.806	(1.12)
Flow$_{t-4:t-1}$ (%)	-0.049	(-1.20)	-0.053	(-1.49)	-0.056	(-1.38)
Expenses$_{t-4:t-1}$ (%)	-5.994*	(-1.65)	-1.344	(-0.28)	-1.115	(-0.25)
Log Size$_{t-1}$	-0.825*	(-1.95)	-0.806**	(-2.37)	-0.594**	(-2.26)
Investment Obj Code 2 (Agg. Growth)	-0.016	(-0.10)	-0.059	(-0.37)	-0.001	(-0.01)
Investment Obj Code 3 (Growth)	-0.027	(-0.29)	-0.065	(-0.68)	-0.011	(-0.14)
Investment Obj Code 4 (Growth & Income)	-0.086	(-0.71)	-0.080	(-0.61)	-0.030	(-0.27)
Fund Age Q1 (Youngest)	-0.096	(-1.03)	-0.073	(-0.76)	-0.004	(-0.06)
Fund Age Q2	-0.133	(-1.53)	-0.040	(-0.62)	-0.029	(-0.85)
Fund Age Q3	-0.132	(-1.26)	-0.061	(-0.77)	-0.055	(-1.10)
Fund Age Q4 (Oldest)	-0.092	(-0.92)	0.006	(0.12)	-0.007	(-0.18)
N	46499		45046		40960	
R Sq.	25.68%		36.37%		52.09%	

Table 5 (cont'd)

Panel B: Sharpe Ratios						
All coefficients are x 100	3-month Sharpe $Ratio_{t:t+1}$ (%)	t-stat	6-month Sharpe $Ratio_{t:t+2}$ (%)	t-stat	12-month Sharpe $Ratio_{t:t+4}$ (%)	t-stat
$SPR_{t-4:t-1}$ (%)	-98.556**	(-2.34)	-59.403***	(-2.73)	-37.619***	(-2.73)
Active $Share_{t-1}$ (%)	11.262	(0.32)	11.778	(0.84)	12.269	(1.46)
Delta Active $Share_{t-1:t}$ (%)	-1.180	(-0.09)	-8.585**	(-2.06)	-4.439	(-1.22)
$Sumret_{t-4:t-1}$ (%)	110.770***	(3.33)	36.354**	(2.16)	21.791**	(2.13)
$Flow_{t-4:t-1}$ (%)	-3.360**	(-1.99)	-0.972*	(-1.73)	-0.725	(-1.27)
$Expenses_{t-4:t-1}$ (%)	-247.371	(-1.48)	-164.796	(-1.58)	-125.043	(-1.51)
Log $Size_{t-1}$	-17.804	(-1.16)	-13.133**	(-2.23)	-9.878**	(-2.42)
Investment Obj Code 2 (Agg. Growth)	-5.319	(-0.76)	-6.782**	(-2.30)	-3.376*	(-1.79)
Investment Obj Code 3 (Growth)	-0.529	(-0.11)	-1.335	(-0.65)	0.188	(0.13)
Investment Obj Code 4 (Growth & Income)	-1.547	(-0.18)	2.733	(0.66)	2.540	(1.04)
Fund Age Q1 (Youngest)	-2.805	(-0.50)	-1.354	(-0.57)	-0.300	(-0.21)
Fund Age Q2	-3.208	(-0.68)	-1.528	(-0.83)	-1.291	(-1.26)
Fund Age Q3	-3.794	(-0.70)	-1.026	(-0.43)	-1.465	(-1.22)
Fund Age Q4 (Oldest)	-3.132	(-0.65)	0.616	(0.29)	-0.155	(-0.14)
N	46498		45046		40960	
R Sq.	12.43%		39.33%		56.74%	

Panel C: Alphas				
All coefficients are x 100	Holdings Alpha (12-month) $_{t:t+4}$ (%)	t-stat	Holdings Alpha (36-month) $_{t:t+12}$ (%)	t-stat
$SPR_{t-4:t-1}$ (%)	-0.340	(-0.81)	-0.527**	(-2.03)
Active $Share_{t-1}$ (%)	0.101	(0.54)	0.128	(1.47)
Delta Active $Share_{t-1:t}$ (%)	0.010	(0.19)	-0.005	(-0.14)
$Sumret_{t-4:t-1}$ (%)	0.242	(0.80)	0.135	(0.53)
$Flow_{t-4:t-1}$ (%)	-0.039**	(-2.22)	-0.023**	(-2.37)
$Expenses_{t-4:t-1}$ (%)	-0.336	(-0.19)	-0.202	(-0.14)
Log $Size_{t-1}$	-0.178	(-1.19)	-0.207	(-1.54)
Investment Obj Code 2 (Agg. Growth)	0.006	(0.10)	-0.022	(-0.53)
Investment Obj Code 3 (Growth)	-0.007	(-0.29)	-0.009	(-0.36)
Investment Obj Code 4 (Growth & Income)	-0.032	(-0.83)	-0.035	(-1.39)
Fund Age Q1 (Youngest)	0.024	(0.58)	-0.027	(-0.91)
Fund Age Q2	0.005	(0.17)	-0.045*	(-1.84)
Fund Age Q3	-0.008	(-0.30)	-0.031*	(-1.68)
Fund Age Q4 (Oldest)	0.006	(0.16)	-0.028	(-1.38)
N	36141		31697	
R Sq.	12.15%		10.98%	

Table 5 (cont'd)

Panel D: Information Ratios				
All coefficients are x 100	Holdings Information Ratio (12-month) $_{t:t+4}$ (%)	t-stat	Holdings Information Ratio (36-month) $_{t:t+12}$ (%)	t-stat
$SPR_{t-4:t-1}$ (%)	-22.504	(-0.76)	-24.547**	(-2.36)
Active Share $_{t-1}$ (%)	13.968	(0.89)	10.395	(1.31)
Delta Active Share $_{t-1:t}$ (%)	5.560	(0.74)	2.124	(0.77)
$Sumret_{t-4:t-1}$ (%)	9.016	(0.42)	9.200	(0.90)
$Flow_{t-4:t-1}$ (%)	-1.939*	(-1.84)	-0.969**	(-2.01)
$Expenses_{t-4:t-1}$ (%)	-200.066	(-1.33)	-156.554**	(-2.01)
Log $Size_{t-1}$	-5.039	(-0.48)	-5.848	(-0.86)
Investment Obj Code 2 (Agg. Growth)	-3.465	(-0.98)	-4.038*	(-1.73)
Investment Obj Code 3 (Growth)	-3.432*	(-1.77)	-2.955**	(-2.02)
Investment Obj Code 4 (Growth & Income)	-6.760	(-1.62)	-4.766***	(-2.92)
Fund Age Q1 (Youngest)	0.295	(0.09)	-2.330	(-1.27)
Fund Age Q2	1.067	(0.38)	-2.018	(-1.22)
Fund Age Q3	1.109	(0.48)	-1.259	(-0.94)
Fund Age Q4 (Oldest)	0.969	(0.33)	-1.936	(-1.28)
N	36141		31697	
R Sq.	8.82%		10.53%	

Table 6

Dynamics of Across-Industry and Within-Industry Active Share

The table reports the regression of *Delta Across-Industry Active Share* (*AIAS*) and *Delta Within-Industry Active Share* (*WIAS*). *Delta AIAS* and *Delta WIAS* are the log *AIAS* and log *WIAS* of the reported portfolio minus the corresponding measure of a hypothetical portfolio had the manager not traded in the quarter. *Across-Industry Active Share* (*AIAS*) is calculated as one half of the sum of absolute deviations in industry weights of an active portfolio from its benchmark index. *Within-Industry Active Share* (*WIAS*) is the average deviation within a typical industry.

SPR is the sum of positive monthly benchmark-adjusted returns in the past 12 months. *Sumret* is the sum of monthly benchmark-adjusted returns in the past 12 months. *Tracking Error* (12-*month*) is the standard deviation of the benchmark-adjusted returns in the past 12 months. *Flow* is the annual flow divided by the total net assets. *Unrealized Gains* are the cumulative unrealized gains divided by total purchase value. *Turnover* is the annual sum of all purchases and sales divided by the value of total holdings. *Expenses* is the annual expense ratio. *Investment Obj Code* 2 - 4 are investment objective code dummies (2 = aggressive growth, 3 = growth, 4 = growth and income). *Fund Age* Q1 - Q4 and *Size Q1* - *Q4* are, respectively, the age and total net asset quartile dummies (1 = youngest or largest). The subscript t represents quarter t and the timing of the variables (e.g., *Delta Active Share* $_{t\text{-}1:t}$ is calculated from quarter t-1 to t). Intercepts and estimates on the year dummies are not reported.

Heteroskedasticity-consistent time- and fund-clustered t-statistics are in parentheses. *, ** and *** denote 10%, 5% and 1% significance, respectively.

All coefficients are x 100	Delta $AIAS_{t\text{-}1:t}$ (%)	t-stat	Delta $WIAS_{t\text{-}1:t}$ (%)	t-stat
$SPR_{t\text{-}4:t\text{-}1}$ (%)	0.388	(0.09)	9.430***	(2.88)
$Sumret_{t\text{-}4:t\text{-}1}$ (%)	-0.070	(-0.03)	-2.496*	(-1.66)
Tracking Error (12-month) $_{t\text{-}4:t\text{-}1}$ (%)	4.192	(0.39)	0.352	(0.04)
$Flow_{t\text{-}4:t\text{-}1}$ (%)	-0.608*	(-1.65)	-1.127	(-1.56)
Unrealized Gains $_{t\text{-}1}$ (%)	0.826	(1.22)	0.232	(0.68)
$Turnover_{t\text{-}4:t\text{-}1}$ (%)	-0.276**	(-2.18)	-0.151	(-0.84)
$Expenses_{t\text{-}4:t\text{-}1}$ (%)	40.531**	(2.19)	68.661***	(3.04)
Investment Obj Code 2 (Agg. Growth)	-1.924	(-0.07)	40.191	(1.08)
Investment Obj Code 3 (Growth)	51.421**	(2.25)	70.009**	(2.00)
Investment Obj Code 4 (Growth & Income)	57.267**	(2.45)	71.261*	(1.74)
Fund Age Q1 (Youngest)	-63.417	(-1.21)	-39.569	(-1.00)
Fund Age Q2	-55.079	(-1.33)	-21.455	(-0.53)
Fund Age Q3	-61.425	(-1.30)	-38.435	(-1.10)
Fund Age Q4 (Oldest)	-44.761	(-1.08)	-13.073	(-0.48)
Size Q1 (Largest)	47.000	(0.42)	-26.881	(-0.41)
Size Q2	46.343	(0.42)	-20.345	(-0.30)
Size Q3	45.532	(0.38)	-43.216	(-0.57)
Size Q4 (Smallest)	51.805	(0.45)	-33.273	(-0.43)
N	46510		46510	
R Sq.	2.22%		1.95%	

Table 7
Regression of Future Performance Measures on Across-Industry and Within-Industry Active Share

This table shows the results of the regression of future fund performance measures on *SPR* and *Across-Industry Active Share* (*AIAS*) and *Within-Industry Active Share* (*WIAS*). All performance measures are calculated based on pre-expense returns from CRSP. The measures are *Realized Alpha* (12-*month*) and *Realized Alpha* (36 - *month*) in Panel A, and *Realized Information Ratio* (12-month) and *Realized Information Ratio* (36-month) in Panel B. *Realized Alpha* is the alpha calculated based on the regression of monthly excess returns on the monthly four factors. *Realized Information Ratio* is the ratio of *Realized Alpha* to the standard deviation of regression residuals.

SPR is the sum of positive monthly benchmark-adjusted returns in the past 12 months. *Across-Industry Active Share* (*AIAS*) is calculated as one half of the sum of absolute deviations in industry weights of an active portfolio from its benchmark index. *Within-Industry Active Share* (*WIAS*) is the average deviation within a typical industry. *Delta AIAS* and *Delta WIAS* are the log *AIAS* and log *WIAS* of the reported portfolio minus the corresponding measure of a hypothetical portfolio had the manager not traded in the quarter. *Sumret* is the sum of monthly benchmark-adjusted returns in the past 12 months. *Flow* is the annual flow divided by the total net assets. *Expenses* is the annual expense ratio. *Size* is the total net assets of the fund. *Investment Obj Code* 2 - 4 are investment objective code dummies (2 = aggressive growth, 3 = growth, 4 = growth and income). *Fund Age* $Q1$ - $Q4$ are the age quartile dummies (1 = youngest). The subscript t represents quarter t and the timing of the variables (e.g., *Realized Alpha* (60-*month*)$_{t:t+19}$ is calculated from quarter t to t+19). Intercepts and estimates on the year dummies are not reported.

Heteroskedasticity-consistent time- and fund-clustered t-statistics are in parentheses. *, ** and *** denote 10%, 5% and 1% significance, respectively.

Panel A: Alphas				
All coefficients are x 100	Realized Alpha (12-month)$_{t:t+4}$ (%)	t-stat	Realized Alpha (36-month)$_{t:t+12}$ (%)	t-stat
SPR$_{t-4:t-1}$ (%)	-0.817**	(-2.27)	-0.904***	(-3.14)
Across-Industry Active Share $_{t-1}$ (%)	0.432***	(3.59)	0.377***	(3.59)
Delta AIAS$_{t-1:t}$ (%)	0.048	(1.32)	0.041*	(1.71)
Within-Industry Active Share $_{t-1}$ (%)	0.052	(0.27)	0.094	(0.94)
Delta WIAS$_{t-1:t}$ (%)	-0.044	(-0.89)	-0.046	(-1.13)
Sumret$_{t-4:t-1}$ (%)	0.653**	(2.33)	0.361	(1.32)
Flow$_{t-4:t-1}$ (%)	-0.048**	(-2.28)	-0.030***	(-2.69)
Expenses$_{t-4:t-1}$ (%)	-0.029	(-0.02)	-0.272	(-0.18)
Log Size$_{t-1}$	-0.147	(-0.87)	-0.140	(-0.90)
Investment Obj Code 2 (Agg. Growth)	0.023	(0.42)	0.014	(0.39)
Investment Obj Code 3 (Growth)	0.005	(0.15)	0.007	(0.23)
Investment Obj Code 4 (Growth & Income)	-0.007	(-0.19)	-0.012	(-0.41)
Fund Age Q1 (Youngest)	0.077*	(1.70)	0.025	(0.75)
Fund Age Q2	0.019	(0.61)	-0.039	(-1.43)
Fund Age Q3	-0.013	(-0.54)	-0.030	(-1.58)
Fund Age Q4 (Oldest)	-0.006	(-0.20)	-0.044**	(-2.01)
N	39457		33305	
R Sq.	9.94%		8.97%	

Table 7 (cont'd)

Panel B: Information Ratios				
All coefficients are x 100	Realized Information Ratio (12-month) $_{t:t+4}$ (%)	t-stat	Realized Information Ratio (36-month) $_{t:t+12}$ (%)	t-stat
$SPR_{t-4:t-1}$ (%)	-1.841	(-0.09)	-38.266***	(-3.69)
Across-Industry Active Share $_{t-1}$ (%)	12.012*	(1.93)	16.527***	(2.87)
Delta $AIAS_{t-1:t}$ (%)	-2.739	(-0.86)	1.991	(1.41)
Within-Industry Active Share $_{t-1}$ (%)	-0.182	(-0.03)	11.948**	(2.14)
Delta $WIAS_{t-1:t}$ (%)	-3.860	(-0.58)	0.008	(0.00)
$Sumret_{t-4:t-1}$ (%)	0.111	(0.01)	18.615	(1.63)
$Flow_{t-4:t-1}$ (%)	-2.111**	(-2.47)	-1.153**	(-2.42)
$Expenses_{t-4:t-1}$ (%)	-70.938	(-0.73)	-81.894	(-0.93)
Log $Size_{t-1}$	-13.175**	(-2.20)	-5.744	(-0.73)
Investment Obj Code 2 (Agg. Growth)	3.809*	(1.65)	-1.181	(-0.50)
Investment Obj Code 3 (Growth)	1.855	(1.23)	-1.050	(-0.64)
Investment Obj Code 4 (Growth & Income)	-0.924	(-0.38)	-2.529	(-1.36)
Fund Age Q1 (Youngest)	1.840	(0.77)	0.075	(0.03)
Fund Age Q2	-0.618	(-0.28)	-2.055	(-1.14)
Fund Age Q3	-1.626	(-1.22)	-1.191	(-0.81)
Fund Age Q4 (Oldest)	-1.900	(-0.94)	-2.751*	(-1.74)
N	39457		33305	
R Sq.	4.24%		10.66%	

Table 8

Correlation between Industry Weights and Within-Industry Deviations

The table reports the regression of *Corr*(*Ind Wght*, *Deviation*) on *SPR* (Sum of Positive Returns), the sum of benchmark-adjusted returns, and other fund characteristics. *Corr*(*Ind Wght*, *Deviation*) is the correlation between benchmark-adjusted industry weights and within-industry deviations from the benchmark.

SPR is the sum of positive monthly benchmark-adjusted returns in the past 12 months. *Sumret* is the sum of monthly benchmark-adjusted returns in the past 12 months. *Tracking Error* (12-*month*) is the standard deviation of the benchmark-adjusted returns in the past 12 months. *Flow* is the annual flow divided by the total net assets. *Unrealized Gains* are the cumulative unrealized gains divided by total purchase value. *Turnover* is the annual sum of all purchases and sales divided by the value of total holdings. *Expenses* is the annual expense ratio. *Investment Obj Code* 2 - 4 are investment objective code dummies (2 = aggressive growth, 3 = growth, 4 = growth and income). *Fund Age* $Q1$ - $Q4$ and *Size* $Q1$ - $Q4$ are, respectively, the age and total net asset quartile dummies (1 = youngest or largest). The subscript t represents quarter t and the timing of the variables (e.g., $Corr(Ind\ Wght, Deviation)_t$ is calculated in quarter t). Intercepts and estimates on the year dummies are not reported.

Heteroskedasticity-consistent time- and fund-clustered t-statistics are in parentheses. *, ** and *** denote 10%, 5% and 1% significance, respectively.

All coefficients are x 100

	Corr(Ind Wght, Deviation) $_t$ (%)	t-stat	Corr(Ind Wght, Deviation) $_t$ (%)	t-stat
$SPR_{t-4:t-1}$ (%)	-17.026***	(-5.89)	-15.468***	(-3.42)
$Sumret_{t-4:t-1}$ (%)	6.912***	(3.18)	5.679**	(2.29)
Tracking Error (12-month) $_{t-4:t-1}$ (%)			19.606	(1.38)
Corr(Ind Wght, Deviation) $_{t-1}$ (%)	58.215***	(38.98)	57.324***	(38.25)
$Flow_{t-4:t-1}$ (%)			0.346*	(1.68)
Unrealized Gains $_{t-1}$ (%)			0.525	(0.42)
$Turnover_{t-4:t-1}$ (%)			-1.375***	(-4.88)
$Expenses_{t-4:t-1}$ (%)			-34.083	(-0.89)
Investment Obj Code 2 (Agg. Growth)			-213.214***	(-2.99)
Investment Obj Code 3 (Growth)			-117.709***	(-2.41)
Investment Obj Code 4 (Growth & Income)			-73.667	(-1.33)
Fund Age Q1 (Youngest)			127.754*	(1.91)
Fund Age Q2			156.694**	(2.50)
Fund Age Q3			98.085*	(1.91)
Fund Age Q4 (Oldest)			193.750***	(5.71)
Size Q1 (Largest)			50.953	(0.20)
Size Q2			-0.416	(-0.00)
Size Q3			-17.060	(-0.07)
Size Q4 (Smallest)			-14.909	(-0.06)
N	46508		46508	
R Sq.	42.03%		42.61%	

Table 9
Robustness Test: Regression of Change in Turnover on SPR

The table reports the regression of the change in turnover on *SPR* (Sum of Positive Returns), the sum of benchmark-adjusted returns, and other fund characteristics. The dependent variable is *Delta Turnover* (12-*month*). *Turnover* (12-*month*) is the annual sum of all purchases and sales divided by the value of total holdings. *Delta Turnover* is the *Turnover* (12-*month*) from quarter t to t+3 minus the *Turnover* (12-*month*) from quarter t-4 to t-1.

SPR is the sum of positive monthly benchmark-adjusted returns in the past 12 months. *Sumret* is the sum of monthly benchmark-adjusted returns in the past 12 months. *Tracking Error* (12-*month*) is the standard deviation of the benchmark-adjusted returns in the past 12 months. *Flow* is the annual flow divided by the total net assets. *Unrealized Gains* are the cumulative unrealized gains divided by total purchase value. *Expenses* is the annual expense ratio. *Investment Obj Code* 2 - 4 are investment objective code dummies (2 = aggressive growth, 3 = growth, 4 = growth and income). *Fund Age* $Q1$ - $Q4$ and *Size* $Q1$ - $Q4$ are, respectively, the age and total net asset quartile dummies (1 = youngest or largest). The subscript t represents quarter t and the timing of the variables (e.g., $SPR_{t\text{-}4:t\text{-}1}$ is calculated from quarter t-4 to t-1). Intercepts and estimates on the year dummies are not reported.

Heteroskedasticity-consistent time- and fund-clustered t-statistics are in parentheses. *, ** and *** denote 10%, 5% and 1% significance, respectively.

All coefficients are x 100	Delta Turnover (12-month) (%)	t-stat	Delta Turnover (12-month) (%)	t-stat
$SPR_{t-4:t-1}$ (%)	117.963***	(5.90)	144.281***	(3.20)
$Sumret_{t-4:t-1}$ (%)	-63.584***	(-3.40)	-77.482**	(-2.50)
Tracking Error (12-month) $_{t-4:t-1}$ (%)			-234.982	(-1.45)
$Flow_{t-4:t-1}$ (%)			-0.259	(-0.14)
Unrealized Gains $_{t-1}$ (%)			-17.949**	(-2.47)
$Turnover_{t-4:t-1}$ (%)	-39.506***	(-14.90)	-41.250***	(-14.69)
$Expenses_{t-4:t-1}$ (%)			401.648**	(2.13)
Investment Obj Code 2 (Agg. Growth)			11.524***	(2.95)
Investment Obj Code 3 (Growth)			4.480	(1.40)
Investment Obj Code 4 (Growth & Income)			-4.526	(-1.43)
Fund Age Q1 (Youngest)			8.094**	(2.01)
Fund Age Q2			3.000	(0.87)
Fund Age Q3			1.084	(0.49)
Fund Age Q4 (Oldest)			0.284	(0.10)
Size Q1 (Largest)			-9.894	(-0.90)
Size Q2			-6.210	(-0.56)
Size Q3			-2.219	(-0.19)
Size Q4 (Smallest)			-9.899	(-0.85)
N	45756		45756	
R Sq.	10.59%		10.90%	

Table 10

Robustness Test: Regression of Fund Flows on SPR

The table reports the regression of fund flows on *SPR* (Sum of Positive Returns), the sum of benchmark-adjusted returns, and other fund characteristics. The dependent variable is *Flow*, which is the dollar flow into the mutual fund divided by its total net assets.

SPR is the sum of positive monthly benchmark-adjusted returns in the past 12 months. *Sumret* is the sum of monthly benchmark-adjusted returns in the past 12 months. *Tracking Error* (12-*month*) is the standard deviation of the benchmark-adjusted returns in the past 12 months. *Unrealized Gains* are the cumulative unrealized gains divided by total purchase value. *Turnover* is the annual sum of all purchases and sales divided by the value of total holdings. *Expenses* is the annual expense ratio. *Investment Obj Code* 2 - 4 are investment objective code dummies (2 = aggressive growth, 3 = growth, 4 = growth and income). *Fund Age* $Q1$ - $Q4$ and *Size* $Q1$ - $Q4$ are, respectively, the age and total net asset quartile dummies (1 = youngest or largest). The subscript t represents quarter t and the timing of the variables (e.g., $SPR_{t\text{-}4:t\text{-}1}$ is calculated from quarter t-4 to t-1). Intercepts and estimates on the year dummies are not reported.

Heteroskedasticity-consistent time- and fund-clustered t-statistics are in parentheses. *, ** and *** denote 10%, 5% and 1% significance, respectively.

All coefficients are x 100	Flow (3-month) $_{t\text{-}1:t}$ (%)	t-stat	Flow (3-month) $_{t\text{-}1:t}$ (%)	t-stat
$SPR_{t\text{-}4:t\text{-}1}$ (%)	1.617	(0.36)	-15.942	(-1.47)
$Sumret_{t\text{-}4:t\text{-}1}$ (%)	24.701***	(5.78)	33.885***	(3.99)
Tracking Error (12-month) $_{t\text{-}4:t\text{-}1}$ (%)			71.969	(1.55)
$Flow_{t\text{-}4:t\text{-}1}$ (%)	6.004***	(14.15)	5.461***	(11.74)
Unrealized Gains $_{t\text{-}1}$ (%)			2.759**	(2.32)
$Turnover_{t\text{-}4:t\text{-}1}$ (%)			0.002	(0.01)
$Expenses_{t\text{-}4:t\text{-}1}$ (%)			-60.282*	(-1.80)
Investment Obj Code 2 (Agg. Growth)			-1.024*	(-1.89)
Investment Obj Code 3 (Growth)			-0.727*	(-1.76)
Investment Obj Code 4 (Growth & Income)			-0.816**	(-2.15)
Fund Age Q1 (Youngest)			2.861***	(5.23)
Fund Age Q2			0.605	(0.92)
Fund Age Q3			-0.369	(-0.61)
Fund Age Q4 (Oldest)			-0.217	(-0.43)
Size Q1 (Largest)			-1.753	(-1.50)
Size Q2			-2.014*	(-1.66)
Size Q3			-1.263	(-1.07)
Size Q4 (Smallest)			0.706	(0.56)
N	46508		46508	
R Sq.	6.37%		7.29%	