# Fund Manager Conviction and Investment Performance

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**Abstract**

This paper examines the role conviction plays in asset management and its relationship with investment returns. We measure the strength of fund manager conviction through a fund's Active Share, i.e., the extent to which an investment portfolio differs from its benchmark index. First, we show fund manager conviction increases following both superior and, surprisingly, inferior past performance, and more so among solo-managed than team-managed funds. Second, and more importantly, we find an inverse-U relationship between conviction and subsequent performance. High levels of conviction proxied by high Active Share are associated with lower future returns and greater fund risk. Our study also illustrates an asymmetric investor reaction to fund manager conviction in the form of higher (lower) fund inflows rewarding good performance by high (low) conviction managers, but no pronounced penalties for poor performance, *ceteris paribus*.

**Keywords**: Overconviction; Uncertainty; Active Share; Fund performance; Fund flows; Fund structure
**JEL:** G11, G23, G41

The authors are from Lancaster University, University of Warwick, and Cardiff University respectively. We are grateful to Amit Goyal, Alok Kumar, April Klein, Andy Adams, Michael Moore, Hersh Shefrin, Peter Bodycombe, Sohnke Bartram, Martijn Cremers, Ben Jacobsen, Haim Kassa, Esther Lee, Miles Livingston, Sarah Maynard, Tao Li and the participants at the Inquire UK Conference in London, the CFA Behavioural Finance Conference in London, the Behavioural Finance Working Group Conference in London, the EFMA Annual Conference in Basel, the FMA Global Meeting in Las Vegas, the Academy of Behavioral Finance and Economics Conference in Stuttgart, the INFINITI Conference in Poznan, and research seminar participants at Aarhus University, Heriot-Watt University, University of Stirling, and University of Portsmouth for their helpful discussions and comments. All remaining errors are our responsibility. Address correspondence to Richard Taffler, Warwick Business School, The University of Warwick, Coventry CV4 7AL, UK, email: Richard.Taffler@wbs.ac.uk

# 1. INTRODUCTION

Fund managers are paid to make investment decisions but operate in an environment where outcomes are inherently uncertain and thus difficult if not impossible to predict *ex ante*. This leads to a situation of ambivalence (Smelser, 1998) or emotional conflict and potential stasis. “The issue is not which choice is optimal [which is impossible to know in advance], but how can you come to a decision at all” (Chong and Tuckett, 2015 p. 314; brackets added). The psychological challenge for asset managers is to be able to convince themselves that a proposed action will be profitable rather than lead to loss; overcoming this conflict is essentially an emotional process beyond the possibility of any rational calculus. Given the impossible task of correctly guessing the future even in probabilistic terms, being able to develop the necessary degree of conviction to act in such a situation of radical uncertainty is key. In this paper we explore the relation between level of fund manager conviction and fund returns.

This study, to our knowledge, is the first to introduce the concept of investor conviction to the empirical finance literature and then to test its implications in terms of future investment performance. Also, it is the first paper to examine the ‘dark side’ of overconviction among fund managers, as proxied by Active Share, i.e., the extent to which an investment portfolio differs from its benchmark index. We provide an empirical analysis rooted in behavioural finance that extends Frazzini et al. (2016)’s critique of Active Share.

A large number of studies already demonstrate that, on average, actively managed equity mutual funds fail to outperform their passive benchmarks net of fees (e.g., Jensen, 1968; Malkiel, 1995; Fama and French, 2010; Gennaioli et al., 2015; Cassavechia and Hulley, 2018); superior fund performance does not persist over time (e.g., Carhart, 1997; Barras et al., 2010; Busse et al., 2010; Cuthbertson et al., 2016); and that mutual fund managers are similarly, albeit to a lesser extent, subject to behavioural biases, sentiment and herding (see, e.g., Wintoki and Xi, 2019; Hudson et al., 2020). Many such observations also apply to mutual funds in other asset classes; for example, bond mutual funds similarly fail to show persistence of superior performance (see, e.g., Gallo et al., 1997; Clare et al., 2019). However, less work has been done on investigating possible systematic factors that drive fund underperformance. In particular, the role emotional processes play in helping to explain fund returns has been largely overlooked to date in the empirical literature despite emotions playing a major part in all financial decision making (e.g., Pixley, 2004, 2009; Tuckett and Taffler, 2012; Aggarwal, 2014). Most previous work on mutual fund performance implicitly assumes fund managers are sophisticated investors who gather and process information efficiently and behave ‘rationally’. However, such appealingly simple descriptions do not represent what professionals in the asset management industry actually experience and do, and what really drives their investment decisions (e.g., Taffler et al., 2017).

The asset management industry represents a highly emotional environment. Fund managers are under intense pressure to outperform their often equally able peers; they are swamped with incomplete information that is often conflicting and open to competing interpretations; and, ultimately, they have to make investment decisions by relying on subjective judgements and beliefs (Tuckett and Taffler, 2012). Conviction is recognized by practitioners as a vital ingredient in the investment process as illustrated, *inter alia*, in how fund managers commonly describe what drives their investment decisions.[1,2] The uncertainty of investment outcomes and associated high level of anxiety leads to cognitive and emotional conflicts which financial actors overcome by constructing "conviction narratives" about imagined "desired outcomes" (Chong and Tuckett, 2015; Tuckett and Nikolic, 2017). Thus, being able to generate necessary levels of conviction or faith to be able to act is a *sine qua non* of all investment activity.

In contrast to overconfidence, which is viewed as a behavioral or cognitive bias by psychologists and finance academics, and takes a number of different and often conflicting forms (e.g., Moore and Healy, 2008; Forbes et al., 2015; Kariofyllas et al., 2017; Merkle, 2017), we argue that level of conviction is a more accurate descriptor of what drives actual fund manager investment decisions. This is because conviction addresses underlying beliefs and the conscious and, more importantly, unconscious threats and anxieties associated with an environment where there is no known 'right' answer and there are real and potentially very adverse consequences associated with underperformance. This is a quite different context to the conventional and often laboratory-based decision situations cognitive psychologists deal with where 'correct' answers are typically knowable.[3]

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[1] Such as "high conviction", "absolute conviction", "conviction ideas", "developing conviction" (Chong and Tuckett, 2015). Cohen et al. (2010) in fact start their paper by describing how when a fund manager is asked to discuss his portfolio he will "…describe the opportunity and investment thesis with tremendous conviction and enthusiasm … [with the listener] frequently overwhelmed by the persuasiveness of the presentation (p. 1)." See also Siegel and Scanlan (2014).

[2] Definitions in the academic literature include "… the willingness to take risk and express beliefs through a bold course of action, in pursuit of long-term goals" (Sebastian and Attaluri, 2014) and "… the willingness to translate identified investment opportunities into a portfolio that is sufficiently different to outperform in the long term" (Cremers, 2017). However, the sense remains that the concept is a more subtle and emotionally driven one and is more of the form that 'you know it when you see it' with the term generally used loosely (e.g., Cremers and Pareek, 2016).

[3] There is, however, a limited amount of work which examines fund manager performance from a behavioral perspective and in particular the potential role of overconfidence and associated self-attribution bias (e.g., Puetz and Ruenzi, 2011). However, such a perspective is based on the idea that the 'right' investment decision can in some sense be known before it has played out rather than that this is unpredictable. It is not possible to be confident in any meaningful sense when outcomes are effectively beyond one's control; in such situations of radical uncertainty the only way it is possible to act is by having faith or conviction that what you want to happen will in fact occur even if

The main contribution of our paper is showing that fund manager conviction as proxied by their Active Share is associated with subsequent investment returns in a non-linear way. We expect high conviction fund managers will mentally downplay or repress the inherent lack of predictability of their investment outcomes and concentrate their holdings in stocks where the conviction narratives they are able to build seem most persuasive. In parallel, they will excessively underweight their holdings in other stocks where they are unable to construct such seemingly plausible investment stories. This can then result in their portfolios deviating too far from their benchmark indices harming portfolio performance. Conversely, low conviction fund managers unable to generate sufficient conviction to overcome the underlying uncertainties and associated anxieties of the investment process to be able to act will find difficulty in deviating significantly from their benchmark holdings and thus also underperform after fees. Overall, we posit that, if high Active Share is mainly driven by fund manager 'overconviction', we should observe inferior subsequent investment performance for portfolios with high Active Share. Likewise, if funds suffer from 'underconviction' we should find funds with low Active Share also underperforming.

By analyzing a large sample of US actively managed equity mutual funds, we find a clear U-shaped relationship between past performance of funds and their subsequent Active Share. We find robust evidence that fund managers increase their Active Share after experiencing good performance. Interestingly, fund managers suffering poor prior performance also deviate more from their benchmark, possibly reflecting a tendency towards gambling-type behavior in an attempt to catch up (e.g., Brown et al., 1996; Kempf et al., 2009) or seeking to avoid significant fund outflows (Ha and Ko, 2017). Additionally, we find this effect is more pronounced among solo-managed funds which irrespective of prior performance manifest a significantly higher Active Share on average than team-managed mutual funds. This observation is consistent with the idea that conviction relates more to the beliefs of individuals rather than groups where other psychological processes come into play (e.g., Janis, 1982).

Our expectation that both high Active Share and low levels of Active Share are associated with lower subsequent returns implies that there is an 'optimal' range of Active Share which depends on the type of fund, i.e., there is an inverse-U relationship between fund manager performance and Active Share. If we find such a relationship, then that would be consistent with Active Share proxying for level of fund manager conviction.

Our paper examines empirically the potential impact of fund manager conviction on subsequent fund performance. Our results show that excessive levels of conviction, as measured by high Active Share, are

on one level you know it might not. In fact, in such decision situations the term 'confidence' is potentially misleading and really relates to 'conviction'.

significantly associated with diminished future investment returns as is underconviction or index-hugging.[4] Interestingly, fund managers with 'realistic' levels of conviction, as measured by non-extreme levels of Active Share, appear to be able to deliver superior performance.

This study has important policy implications. Based on existing studies (e.g., Cremers and Petajisto, 2009; Petajisto, 2013), regulators such as the UK Financial Conduct Authority argue that the level of Active Share in actively managed mutual funds should be maximized on the basis that this is what investors are paying for (FCA 2016, pp.100-102; 2017, pp.39-40). However, in contrast, our empirical results suggest investors should seek to invest in moderate Active Share funds consistent with an appropriate level of fund manager conviction. Such levels of Active Share might better reflect necessary levels of conviction for fund managers to be able to invest in an appropriate manner, rather than them either denying, consciously or not, the inherent challenges of the investment task leading to unrealistic levels of belief, or being too anxious to be able to act. Such well-motivated trading activities appear empirically to lead to the realization of better portfolio allocation, and better subsequent performance. Further, we find a negative and significant relationship between changes in Active Share rank and subsequent performance which is consistent with our main proposition that too much and too little conviction are both associated with lower future returns. Additionally, our results show a clear non-linear relation between Active Share and fund risk as proxied by both performance extremity and performance dispersion. This indicates that high levels of conviction are associated with more extreme outcomes, greater performance dispersion, and disproportionately increased downside risk.

Our final research question concerns how investors process fund manager conviction signals. Given the problems associated with the *ex ante* choice of subsequently outperforming mutual funds, we would expect investors to rely on noisy signals such as fund manager conviction as a proxy for active investment skill. In other words, we hypothesize that investors 'buy' high conviction fund managers. In fact, our results are consistent with this expectation. In particular, we find that when past performance is positive there are significantly higher fund inflows to high Active Share fund managers. On the other hand, fund outflows from such mutual funds are not significantly greater than lower Active Share funds when past performance is negative. This demonstrates that good performance is a bonus for high Active Share fund managers while there is no pronounced penalty for poor performance, *ceteris paribus*. Investors are not averse to high conviction fund managers even if they lose them money. In this way, our results can shed new light on the determinants of fund flows in the context of investor response to the fund manager Active Share signal.

[4] This latter is consistent with Sherrill et al. (2017) who demonstrate that mutual fund managers who hold excessive ETFs significantly underperform.

The paper progresses as follows. In the next section we discuss our empirical approach and in the following one the mutual fund data we use and the sample selection process. Section 4 describes and interprets the main results and the final section concludes.

## 2. EMPIRICAL APPROACH

### 2.1. Measuring Fund Manager Conviction

Cohen et al. (2010) show that stocks highly weighted in an investment portfolio which they term "high conviction positions" or "best ideas" generate statistically and economically significant risk adjusted returns. However, they do not examine the performance of 'low conviction' stocks. We build on this idea but instead of focusing on individual conviction stocks we examine fund manager conviction at a portfolio level, i.e., 'portfolio conviction' which considers both overweighted and underweighted positions in aggregate. We measure this by the extent to which the investment portfolio deviates from its benchmark portfolio. The basic idea is that fund managers prone to overconviction overweight the stocks in their portfolio in which they have faith and underweight or avoid other stocks, consequently deviating too far from their benchmark indices as reflected in a high level of Active Share.[5]

Essentially, Active Share gauges how much a mutual fund portfolio differs from its benchmark indices. It is defined as half of the sum of absolute deviations in portfolio weight of a fund portfolio from its benchmark index portfolio:

$$Active\ Share_t^{fund} = \frac{1}{2}\sum_{i=1}^{N}\left|weight_{i,t}^{fund} - weight_{i,t}^{index}\right|$$

(Eq. 1)

where $weight_{i,t}^{fund}$ is the weight of stock *i* in the fund's portfolio at time *t*, and $weight_{i,t}^{index}$ is the weight of the same stock *i* in the fund's benchmark index portfolio at time *t*. Active share then is calculated as the sum over the universe of all stock assets.

Determining the relevant benchmark indices for a large sample of mutual funds is not straightforward. Although mutual funds are required by the SEC to disclose their self-declared benchmark indices in their

[5] This concept is distinct from "tracking error" which measures the standard deviation of difference between portfolio returns and the benchmark index returns. High levels of tracking error may be due to concentrated stock picks, but they can also be due to factor bets that do not necessarily proxy for overconviction. For a detailed comparison, see Cremers and Petajisto (2009).

fund prospectuses after 1998, such data are not available in any existing public database. Petajisto (2013) employs few snapshots of the “primary benchmark index” as collected by Morningstar from fund prospectuses. However, these self-declared benchmarks can potentially lead to biased estimations: in order to increase their chances of outperforming the benchmark, fund managers can strategically pick a benchmark index not realistically reflecting the risk exposure of their holdings (e.g., Sensoy, 2009). To avoid this bias, we follow Cremers and Petajisto (2009) who take a different approach to determining the appropriate benchmark index for each of their funds. Specifically, we employ the benchmark index with the lowest Active Share as that fund’s best-fit benchmark.

Prior research has used Active Share as a measure of active management (see, e.g., Cremers and Petajisto, 2009; Petajisto, 2013), and provided evidence consistent with high Active Share predicting superior subsequent performance. However, Active Share levels are implicitly correlated with the investment objectives of the respective portfolios. As the following section shows, Active Share levels vary structurally across funds’ investment objectives so that any apparent positive relationship between high Active Share and superior subsequent performance may simply be due to fund style. In line with this argument, Frazzini et al. (2016) suggest that, in contrast to Cremers and Petajisto (2009) and Petajisto (2013), after controlling for benchmarks, high Active Share funds do not exhibit superior performance.

To mitigate this concern, we employ a modified approach to measure how much a fund manager deviates from his/her benchmark relative to other funds with the same investment style. Specifically, for each quarter, we construct the Active Share rank of a fund by ordering all funds belonging to a specific market segment according to its Active Share. Each fund is then assigned a rank number and this rank number is normalized so that ranks are evenly distributed between 0 and 1. The fund with highest Active Share within its market sector is assigned the rank 1 while the fund with lowest Active Share has the rank 0. This process allows the relative position of any fund to be derived along the active management spectrum compared to all other funds in the same market segment. It also allows us to directly compare funds across different market segments.

### 2.2. Measuring Fund Performance

The main performance measure we use is based on the Carhart (1997) four-factor model which controls for risk and style factors including size, book-to-market and momentum effects. The following regression is estimated:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,M}\left(R_{M,t} - R_{f,t}\right) + \beta_{i,SMB}(SMB_t) + \beta_{i,HML}(HML_t) + \beta_{i,MOM}(MOM_t) + \varepsilon_{i,t}$$

(Eq. 2)

where the dependent variable in the model is the monthly return on mutual fund portfolio *i* at time *t* minus the risk-free rate at time *t*, and the independent variables are the returns of four different zero-investment factor-mimicking portfolios based on excess market return, size, book-to-market ratio and prior performance. Specifically, $R_{M,t} - R_{f,t}$ denotes the excess market return over the risk free rate at time *t*; $SMB_t$ is the return difference between portfolios of stocks with small and large market capitalization at time *t*; $HML_t$ is the return difference between portfolios of stocks with high and low book-to-market ratio at time *t*; $MOM_t$ is the return difference between portfolios of stocks with high and low past performance at time $t$. Using monthly observations of fund returns and factors returns we run the regression for each fund $i$ each year and use the time series of the estimated intercepts for each fund $i$ as its risk-adjusted performance over time. We also estimate the one-factor CAPM alpha, and the Fama and French (1993) three-factor alpha, for robustness tests. The CAPM model uses only the market factor, and the Fama and French (1993) approach employs the first three factors in the model above.

### 2.3. Measuring Performance Extremity

We also examine the realization of extreme performance outcomes by estimating a performance extremity measure based on Bär et al. (2011). These authors examine the effects of the management structure of mutual funds on subsequent risk taking and performance extremity. For each fund *i* in each time period *t*, our performance extremity measure is calculated as the absolute difference between a fund's performance and the average performance of all funds in the same market segment in the same time period. These numbers are then normalized by the average absolute difference of all n funds in the corresponding market segment and respective time period:

$$Perf\ Extremity_{i,t} = \frac{\left|Perf_{i,t} - \overline{Perf}_{i,t}\right|}{\frac{1}{n}\sum_{i=1}^{N}\left|Perf_{i,t} - \overline{Perf}_{i,t}\right|}$$

(Eq. 3)

where $Perf_{i,t}$ denotes the performance of fund portfolio *i* at time period *t*, and $\overline{Perf}_{i,t}$ is the average performance of all funds at the same market segment at time period *t*. The higher the level of performance extremity, the more extreme the performance outcome is, either good or bad. After normalizing the performance extremity measure, a fund with average performance within its market segment, by construction, has a performance extremity of one.

### 2.4. Estimating Fund Flows

To explore our final research question about whether fund flows are positively related with fund manager conviction, we need to measure fund inflows and outflows directly. Following prior literature (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Lou, 2012), we estimate investor net flow for an individual fund share class *i* at time *t* is estimated as:

$$FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGR_{i,t}}{TNA_{i,t-1}}$$

(Eq. 4)

Where $TNA_{i,t}$ is the total net assets for individual fund share class *i* at time *t*; $RET_{i,t}$ is the gross return before expense ratio for individual fund share class *i* at time *t*; $MGR_{i,t}$ is the increase in total net assets for individual fund share class *i* at time *t* due to fund mergers.[6] After adjusting for mutual fund mergers, monthly estimated net flows for all share classes belonging to their common fund are summed to obtain the total fund level monthly estimated net flow. Monthly fund flows during the corresponding quarter are then aggregated on a quarterly basis. We assume that investor inflows and outflows take place at the end of each quarter, and investors reinvest their dividends and capital appreciation distributions in the same fund.

## 3. DATA

### 3.1. Mutual Fund Data

Our mutual fund portfolio holdings and returns data is created by merging the CRSP Survivorship Bias Free Mutual Fund Database with the Thomson Reuters Mutual Fund Holdings Database (formerly known as CDA/Spectrum Database). The CRSP Mutual Fund Database provides information on monthly fund net returns, monthly total net assets, monthly net assets value, different types of fees including annual expense ratio and management fees, turnover ratio, investment objectives, first offer dates and other fund characteristics for each share class of every US open-end mutual fund. Based on mandatory quarterly reports filed with the SEC and voluntary reports generated by the mutual funds themselves, the Thomson

[6] The CRSP Mutual Fund Database does not provide the exact date on which fund mergers occur. We follow Lou (2012) and employ the last net asset value (NAV) report date as the initial estimate of the actual merger date. Then, in order to avoid any obvious mismatches, we match each target individual share class to its acquirer from one month before its last NAV report date to five months later, a total matching period of seven months. Finally, the month in which the acquirer has the smallest absolute percentage net flow, after subtracting the merger, is assigned as the merger event month.

Reuters Mutual Fund Holdings database provides information including fund identification, report date, file date, stock identification, and number of shares held. Information on the returns of each fund in our dataset is then matched to the fund's holdings by using the map provided by the MFLINKS Database.[7] We link each reported stock holding in our mutual fund portfolios to the CRSP stock price database in order to find its stock price information.[8] Active Share data are obtained from www.petajisto.net which is the updated main dataset from Petajisto (2013). A detailed description of how the Active Share dataset we employ is constructed can be found in Petajisto (2013).

### 3.2. Sample Selection

We mainly follow the procedure of Kacperczyk et al. (2005, 2008) to select our US domestic equity mutual fund sample. We start with all mutual funds in the CRSP Mutual Fund Database and the Thomson Reuters Mutual Fund Holdings Database. We then eliminate balanced, bond, money market, international, sector, index, ETF, exchange target, and target date funds as well as those funds not invested primarily in equity securities. To address potential incubation bias, we exclude funds with less than $5 million in total assets under management or holding fewer than 10 stocks. This screening procedure generates a final sample of 80,651 fund-quarter observations for a total of 2,740 unique actively managed mutual funds for the period 1980 to 2009 matching the original Cremers and Petajisto (2009) data.[9]

### 3.3. Summary Statistics

Table 1 presents the descriptive statistics for our fund sample. Panel A reports the total number of domestic equity mutual funds in our sample at 5-year intervals along with fund characteristics. The past three decades witness rapid growth in the size of the mutual fund industry both in terms of number of funds, and average total net assets under management. However, interestingly, average Active Share for our fund sample drops from 90.5% in 1980 to 81.7% in 1990, and to 74.0% in 2009 by the end of our

[7] This database provides the fund's Wharton Financial Institution Center Number (WFICN) that can reliably links fund identification in the CRSP Mutual Fund Database, and portfolio identification in the Thomson Reuters Mutual Fund Holdings Database. We also correct any potential matching errors after this standard data merging procedure by looking at fund names in both databases manually.

[8] Data include stock identification, stock return, delisting return, share price, trading volume, cumulative price adjustment factors, cumulative shares adjustment factors, and shares outstanding as well as other stock characteristics. The number of shares held in the portfolios obtained from the Thomson Reuters Mutual Fund Holdings database are adjusted by the CRSP cumulative shares adjustment factors. There are cases where the Thomson Reuters Mutual Fund Holdings database has already adjusted the number of shares held in the portfolio so in order to track portfolio holdings correctly this paper re-adjusts the number of shares back. We follow the approach of (Daniel and Titman, 1997) to estimate book value of equity for stocks by using shareholder equity (SEQ), deferred taxes (TXDB), investment tax credit (ITCB), and preferred stock (PREF), retrieved from Compustat. Industry classifications (SIC) are obtained from the CRSP stock file and Compustat whenever available.

[9] We use the same sample period and main data set as Cremers and Petajisto (2009) and Frazzini et al. (2016) for result comparison purposes.

sample period. Panel B of Table 1 categorizes our sample funds based on investment objective. Relative to other fund classes, micro-cap funds exhibit the highest Active Share with an average level of 95%, followed by small-cap funds with 85%. These two investment sectors also have the highest expense ratios, perhaps reflecting the cost of their investment styles. On the other hand, growth & income funds and income funds have much lower Active Share levels, and also tend to trade much less actively than funds in other investment objective groups.

Figure 1 illustrates the distribution of Active Share which is highly skewed to the right for micro-cap, small-cap and mid-cap funds. In contrast, growth funds and growth & income funds show a more normal distribution with means in the range of 75-80% and 70-75%, respectively. Such significant structural variation in Active Share by fund investment style can affect the relationship between Active Share and subsequent performance as high Active Share funds may merely reflect their exposure to micro-cap and small-cap funds.

# 4. EMPIRICAL RESULTS

## 4.1. Fund manager Conviction and Past Fund Performance

### *4.1.1. Active Share and Past Performance*

In this section, we examine whether fund manager conviction increases after good past performance by relating this to their level of portfolio conviction in the next period measured in terms of style-adjusted Active Share. The conjecture is that outstanding prior performance might lead fund managers to believe they are better skilled at picking high conviction stocks than they actually are. As a consequence, they overweight those stocks where their conviction narratives are particularly persuasive and underweight or not hold those they (perhaps subjectively) dislike, leading to high levels of Active Share. On the other hand, neither poor performing fund managers nor those with average past performance are likely prone to overconviction. On this basis, we should observe a positive relationship between past performance and Active Share among very successful fund managers with superior past performance but no relationship among average performers.

We first begin by testing for a simple linear relationship between past performance and Active Share level as in Cremers and Petajisto (2009) by running a pooled panel regression of Active Share on past fund performance, and then model the quadratic relationship. Since mutual fund managers are mainly compensated on the basis of total assets under management they are motivated to compete with their peers for inflows. Investors chase relative past performance and thus fund managers are mainly concerned about their relative performance ranking (Sirri and Tufano, 1998). We rank all funds belonging to a specific market segment at the end of each quarter based on prior year returns, and then assign a rank number to each fund. This is then normalized to be equally distributed between 0 and 1.

More importantly, we apply the piecewise linear regression approach to estimate differential slope coefficients for the impact of past performance on Active Share across different ranges of past performance separately. Specifically, three slope coefficients are estimated for the bottom past performance quintile, the three middle past performance quintiles and the top past performance quintile by running the following regression:

$$ActiveShare_{i,t} = \alpha + \beta_1 Perf_{i,t-1}^{LOW} + \beta_2 Perf_{i,t-1}^{MID} + \beta_3 Perf_{i,t-1}^{HGH} + Controls_{i,t-1} + \epsilon_{i,t}$$

(Eq. 5)

Where: $Perf_{i,t-1}^{LOW} = \min(Perf_{i,t-1}, 0.2)$

$Perf_{i,t-1}^{MID} = \min(Perf_{i,t-1} - Perf_{i,t-1}^{LOW}, 0.6)$

$Perf_{i,t-1}^{HGH} = Perf_{i,t-1} - (Perf_{i,t-1}^{LOW} + Perf_{i,t-1}^{MID})$

and $ActiveShare_{i,t}$ denotes the style-adjusted Active Share for fund *i* at quarter *t*, $Perf_{i,t-1}$ is the normalized rank of relative fund past performance for fund *i* at quarter *t*. Fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. $Perf_{i,t-1}^{LOW}$ represents the bottom quintile of past performance rank measured as the normalized rank of fund past performance relative to other funds in the same market segment. $Perf_{i,t-1}^{MID}$ represents the three middle quintiles, and $Perf_{i,t-1}^{HGH}$ represents the top quintile of past performance rank. $Controls_{i,t-1}$ is the vector of control variables relating to fund characteristics. In order to mitigate potential endogeneity, we lag all other control variables by one quarter, except the fund expense and turnover ratios which are lagged one year due to data availability. Control variables include fund age, measured as the natural logarithm of age in years since first offer date; fund size, the natural logarithm of total net assets under management in millions of dollars; expense ratio and turnover ratio measured in percent; tenure calculated as the natural logarithm of current manager's tenure at the fund in years, and fund flow, investor flows estimated by the ratio of $TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - MGR_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers, fund flow and turnover ratio are winsorized at the 1% level.[10]

Table 2 summarizes the results of our regressions of Active Share on past performance. Consistent with Cremers and Petajisto (2009), column (1) shows a positive relationship between past performance and current Active Share after controlling for other fund characteristics and time fixed effects, significant at conventional levels. However, we find the non-linear relationship between past performance and Active Share proxying for fund manager conviction in column (2) dominates the simple linear one. In particular, there is a significant negative coefficient for the linear impact of past performance and a significant positive coefficient for the quadratic term, which indicates a U-shaped relationship between past performance and Active Share.

To explore this non-linear relationship further, results from the piecewise linear regression of Active Share on past performance are presented in column (3). The main focus is on the coefficient for the impact of past performance on subsequent Active Share in the top performance quintile. The estimated coefficient on $Perf_{i,t-1}^{HGH}$ is positive and statistically significant at the 1% level.[11] Assuming all other effects constant, the difference in Active Share between the very best performing fund (rank 1), and a fund at the bottom of the top performance quintile (rank 0.8), is no less than 22% (1.13×0.2=0.22). The estimated coefficient for the three middle performance quintiles is also positive and statistically significant at the 1% level although the magnitude of the effect is much smaller with only 0.9% higher Active Share of funds at the top of the middle performance quintiles (rank 0.8), compared to the funds at the bottom of the middle quintiles (rank 0.2). Interestingly, the coefficient on $Perf_{i,t-1}^{LOW}$ suggests that there is an economically and statistically significant negative relationship between past performance and subsequent performance for the bottom performance quintile. Specifically, holding all other variables constant, the difference in Active Share between a fund at the top of the bottom performance quintile (rank 0.2) and the worst performing fund (rank 0) is large at about -17% (-0.85×0.2=-0.17). This suggests that fund managers suffering from poor past performance are seeking to catch up by deviating more from their respective benchmarks in terms of portfolio holdings in line with gambling behavior. Overall, consistent with the results from our quadratic regression model, our piecewise-linear results demonstrate a

[10] Although we report t-statistics based on standard errors clustered only by fund in line with Cremers and Petajisto (2009) and Puetz and Ruenzi (2011) for result comparability purposes, we also derive standard errors clustered both by fund and time. However, our results are very similar and thus not reported here.

[11] This significant positive relationship between a fund's past performance and its current Active Share holds irrespective of whether we measure past performance using raw fund returns, the one-factor CAPM alpha, or the Fama and French (1993) three factor alpha. The coefficients on $\mathrm{Perf}_{i,t-1}^{HGH}$ are typically significant at the 1% level. This relationship also holds for Active Share unadjusted for fund sector as with Cremers and Petajisto (2009).

U-shaped relationship between past performance and fund manager conviction level as reflected in Active Share. This relationship is clearly presented in Figure 2.A. We repeat the analyses in Table 2 using more recent data from 2010 to 2018. Table A1 in Appendix shows that the findings remain robust.

To investigate whether good past performance is associated with an *increase* in Active Share, we repeat the above regressions with change in Active Share as our dependent variable. Although column (4) of Table 2 shows a significant positive linear relationship between past performance and change in Active Share, the underlying relationship is non-linear. The piecewise regression results in Model (6) show this is primarily driven by the top performance quintile. Plotting our results in Figure 2.B, it is apparent that, compared to an average performer, fund managers with outstanding past performance increase their Active Share by a considerably higher amount of 1.5% per quarter, which supports our expectation that fund managers tend to boost their level of conviction following superior performance.

#### *4.1.2. Solo-managed vs Team-managed Funds*

Team-managed mutual funds are increasingly popular in the industry in recent years (Bär et al., 2011; Adams et al., 2018) although the evidence on whether team-managed funds generate superior returns compared with solo-managed funds is mixed (e.g., Prather and Middleton, 2002, 2006; Bliss et al., 2008; Bär et al., 2011; Goldman et al., 2016). A natural question is to look at how the investment decisions made by teams differ from those of individuals. In the literature, the 'diversification of opinions' hypothesis on the impact of fund management structure suggests that individuals are more prone to idiosyncratic or extreme behavior (Bär et al., 2011). Therefore, if this holds, we would expect solo-managed funds more likely to be influenced by good past performance, and exhibit greater gambling-type behavior after poor prior performance. To test this proposition directly, we investigate the potential difference in responses to past performance between solo-managed and team-managed mutual funds. Specifically, we interact the performance quintiles with a solo management dummy, and adding solo management dummies without interaction to capture the constant effect in our piecewise linear specifications. Results are reported in Table 3.

Model (1) in Table 3 shows that solo-managed mutual funds on average have a 4.6% higher Active Share than funds managed by a team, significant at the 1% level. More interestingly, the effect of past performance on Active Share interacted with the solo dummy for the top performance quintile is positive, and statistically significant at the 10% level. This result is consistent with our argument that, following outstanding performance, the managers of solo-managed funds are more prone to high levels of conviction than their peers managing on a team basis, as reflected by the 2.58% ($0.129\times0.2=0.0258$) higher Active Share of solo-managed funds than their team-managed peers. On the other hand, for the bottom performance quintile, the effect of past performance on Active Share level interacted with the solo dummy is negative, with a 5.5% (-0.276×0.2=-0.052) difference in Active Share between poor performing solo- and team managed funds, statistically significant at the 1% level. This is consistent with the view that the portfolios of solo-managed funds are even more likely to deviate from their benchmark as reflected by their higher Active Share after bad performance. Further results in Model (2) also suggest, broadly speaking, that solo-managed funds tend to increase their Active Share by a higher amount than team-managed funds. Overall, these results of significant difference in Active Share between solo- and team-managed funds directly support the diversification of opinions hypothesis which in our context predicts that solo-managed funds are more subject to strong conviction.

To test the robustness of our results, we use a fund's unconditional Active Share level as in the case of Cremers and Petajisto (2009) as an alternative proxy for fund manager conviction level, and re-run all our regressions of Active Share, and changes in Active Share, on past performance in Table 3. We find consistent results showing that fund managers who experience outstanding performance are more likely to choose a significantly higher level of Active Share, and that they are more likely to increase their Active Share by a larger amount.

We also employ the Fama and MacBeth (1973) approach. This deals with any potential non-independence of observations by analyzing each quarter's observations separately, and therefore will produce more conservative estimates of coefficient significance levels. Our results are all robust in this case as well with similar levels of significance. Our findings thus provide strong evidence that mutual fund managers are prone to overconviction following past success, and such tendency appears to be stronger among solo-managed funds.

### 4.2. Conviction Levels and Subsequent Fund Performance

#### *4.2.1. Conviction and Future Fund Returns*

Our results thus far have shown that outstanding past performance of mutual funds is associated with subsequently increased Active Share. On this basis, we would predict investment decisions driven by too much conviction will also be associated with lower future performance. If this is true, we should observe that high levels of Active Share should be associated with diminished returns, and that overall, we should observe an inverse-U relationship between Active Share and subsequent performance. To explore this potential non-linear relationship, we test the following piecewise linear regression model:

$$Perf_{i,t} = \alpha + \beta_1 ActiveShare_{i,t-1}^{LOW} + \beta_2 ActiveShare_{i,t-1}^{MID} + \beta_3 ActiveShare_{i,t-1}^{HGH}$$

$$+Controls_{i,t-1} + \epsilon_{i,t}$$

(Eq. 6)

Where: $ActiveShare^{LOW}_{i,t-1} = \min(ActiveShare_{i,t-1}, 0.2)$

$ActiveShare^{MID}_{i,t-1} = \min(ActiveShare_{i,t-1} - ActiveShare^{LOW}_{i,t-1}, 0.6)$

$ActiveShare^{HGH}_{i,t-1} = ActiveShare_{i,t-1} - (ActiveShare^{LOW}_{i,t-1} + ActiveShare^{MID}_{i,t-1})$

and the dependent variable, $Perf_{i,t}$, denotes risk-adjusted performance for fund *i* in quarter *t*. Instead of assuming constant factor loadings across time, we use past data to estimate the Carhart (1997) four-factor model and determine the abnormal performance during the subsequent period.[12] Specifically, for each fund in each month, we use 12 past monthly returns to estimate the factor loadings, and subtract the products of factor realizations and estimated factor loadings from the realized return to determine fund abnormal return. We then calculate quarterly abnormal performance for each fund-quarter observation. $ActiveShare^{LOW}_{i,t-1}$ represents the bottom quintile of Active Share rank measured as the normalized Active Share rank of fund *i* relative to other funds in the same segment at the quarter *t-1*, $ActiveShare_{i,t-1}$. $ActiveShare^{MID}_{i,t-1}$ represents the three middle quintiles, and $ActiveShare^{HGH}_{i,t-1}$ represents the top quintile of Active Share rank. We lag all control variables, $Controls_{i,t-1}$, by one quarter, except the expenses and turnover ratios which are lagged one year due to data availability issues. Specifically, as before, we include fund age, fund size, expense ratio, turnover ratio, manager tenure, and prior percentage flow and prior performance. To mitigate the impact of outliers on our estimates, we winsorize flow and turnover ratio at the 1% level. We also include year dummies to capture any time fixed effects and market segment dummies to control segment fixed effects in all regressions. To correctly account for the dependence of observations in our panel data set, we cluster standard errors by fund in all specifications.[13]

Table 4 explores the relationship between Active Share at quarter end and mutual fund performance in the following quarter. The first column shows the coefficient from linear regression of fund future performance on Active Share. In contrast to Cremers and Petajisto (2009) who do not control for different fund styles, we do so and find that Active Share has non-significant predictive power for fund returns. However, when we explore our second research question relating to a potential inverse-U relationship

[12] Recent studies such as Kacperczyk et al. (2005), Ferreira et al. (2013) and others apply a similar approach to measure mutual fund abnormal performance. This approach takes into account possible time variations in the factor loadings of individual funds and avoids the sample selection bias that might arise when excluding young funds without a long return history.

[13] Results are unchanged if we cluster by fund and year.

between Active Share and subsequent fund returns, column (2) shows the expected quadratic relationship. The coefficient for the linear impact of Active Share on subsequent performance is positive while the coefficient for the impact of squared Active Share is negative, with both statistically significant.

More importantly, the regression results for the piecewise linear model in column (3) show that first, the impact of Active Share on subsequent performance is positive but statistically insignificant for the bottom quintile of Active Share. Second, the slope coefficient for the three middle quintiles of Active Share is positive and statistically significant at least at conventional levels, consistent with a significant difference in subsequent performance between a fund at the top of the middle quintiles of Active Share (rank 0.8) and a fund at the bottom of the middle quintiles (rank 0.2). This equates to 18.6 basis points (bps) per quarter (0.0031×0.6=0.00186), or 0.75% on an annual basis, holding other effects constant. Strikingly, the impact of Active Share on subsequent performance is negative for the top quintile of Active Share. As well as being statistically significant, this result is economically significant. On average, funds with the highest segment rank of Active Share underperform funds at the bottom of the top quintile of Active Share by about 27 basis points per quarter (-0.0137×0.2= -0.00274), or 1.1% per year. This quadratic relationship is illustrated graphically in Figure 3.A which plots the derived effects from piecewise linear coefficients (Table 4 column 3) relating to low, middle, and high Active Share funds. Figure 3.B explores these results in more detail based on the model with 9 decile dummies with the lowest 10% Active Share funds as the reference point. This highlights the inverse-U relationship between Active Share and subsequent performance even more clearly with optimal performance manifest in the 0.6 to 0.7 (60% to 70%) Active Share rank range. Overall, Figure  suggests a clear inverse-U-shaped relationship between conviction levels as proxied by Active Share, and subsequent performance. This is consistent with our expectation that ‘moderate’ or realistic levels of fund manager conviction are associated with better subsequent performance while high conviction is significantly associated with diminished future investment returns. We repeat the analyses in Table 4 using more recent data from 2010 to 2018. Table A2 in Appendix shows that the findings remain robust.

To explore this further, we regress fund performance on changes in Active Share in column (4) of Table 4, and find a negative relationship. This again means an increase in Active Share is associated with lower subsequent risk-adjusted abnormal performance. The coefficient on change in Active Share is negative and statistically significant at the 1% level, and the effect is economically meaningful. On average, a 10% increase in Active Share leads to a decrease of subsequent performance by about 9 bps per quarter (-0.0093×0.1= -0.00094) or 37 bps per year. This effect is largely unchanged when considering different quintiles of Active Share in our main regression.

*4.2.2. Conviction and Fund Risk*

Results thus far show that strong conviction as reflected by high Active Share is associated, on average, with lower subsequent fund returns. It is also important to explore the parallel impact of fund manager conviction on fund risk. A fund manager with excessive conviction may take on more risk having faith or belief in their ability to manage this effectively or consciously or unconsciously deny the implications for investment performance. Consequently, high conviction is likely to be associated with extreme (good or bad) subsequent performance. In other words, an increased chance of good performance will also be coupled with a higher probability of underperformance and thus greater idiosyncratic risk.

To investigate this expectation directly, we regress two different measures of fund risk, namely, performance extremity (Bär et al., 2011), and performance dispersion, on Active Share.[14] The piecewise-linear regression in column (3) of Table 5 shows the slope coefficient for the top quintile of Active Share is more than three times as large as those for the three middle and lowest quintiles. This reflects a non-linear relationship between Active Share and performance extremity as illustrated in Figure 4.A (i.e., an increased probability of very good or very bad performance). Similarly, column (8) of Table 5 shows that the standard deviation of performance residuals is positively related with Active Share and, more interestingly, the effect is significantly more pronounced among those fund managers in the top quintile of Active Share, as shown in Figure 4.B. Overall, we find strong evidence showing that strong conviction comes with disproportionately higher fund risk.

The results of these two sub-sections which show that high Active Share is associated with lower future returns and higher risk, taken together, are thus inconsistent with the argument that Active Share is a good measure of fund manager skill.[15]

**4.3. Fund Manager Conviction and Subsequent Fund Flows**

Prior research demonstrates that fund inflows are positively related to past performance but this relationship is asymmetric: investors chase superior past returns but fail to switch from poorly performing funds proportionately (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Ferreira et al., 2012). Such investor responses to fund past performance may potentially be driven by their level of sophistication (Ferreira et al., 2012), as well as fund characteristics such as brand image (Hazenberg et al., 2015), and social responsibility status (Bollen, 2007). However, to the best of our knowledge, there are no

[14] Performance dispersion is measured as the standard deviation of residuals obtained from the Carhart (1997) four-factor model.
[15] However, high Active Share could also potentially be associated with fund manager skill in a subset of cases although this is difficult to measure directly.

empirical studies to date exploring the potential role of fund manager overconviction in driving this non-linear relationship. In this sub-section, we investigate whether, and to what extent, fund investors take fund manager conviction into account as a predictor of future fund performance, and incorporate this information in their investment decisions.

To test this proposition, we first regress net fund flows on fund Active Share with results reported in columns (1) to (3) in Table 6. The coefficient on Active Share in column (1) is positive and statistically significant at the 1% level, suggesting that in general investors chase Active Share, holding all other effects constant. In particular, column (2) demonstrates that this positive linear relationship is mainly driven by the tendency of investors to chase funds in the top Active Share quintile. Mutual fund managers who exhibit highest Active Share attract significantly higher investor flows than those with lowest Active Share by 1.32% per quarter while there is no significant difference in fund flows between the low quintile and the three middle quintiles of Active Share.

However, it is difficult to conclude from these results that the observed influence of Active Share on fund inflows is due to investors treating fund manager conviction as an indicator of future expected returns. We speculate that high Active Share may be misunderstood by investors as an indicator of manager investment skill leading to more pronounced performance-chasing behavior among funds in the top Active Share quintile. To test this directly, we build on Bollen (2007) and estimate the relationship between manager conviction level and investor flows by interacting past performance and Active Share in the following regression:

$$Flow_{i,t} = \alpha + \alpha_1 D^{MID}_{i,t-1} + \alpha_2 D^{HGH}_{i,t-1} + (\beta_1 D^{LOW}_{i,t-1} D^{Neg}_{i,t-1} + \beta_2 D^{MID}_{i,t-1} D^{Neg}_{i,t-1} + \beta_3 D^{HGH}_{i,t-1} * D^{Neg}_{i,t-1} + \beta_4 D^{LOW}_{i,t-1} D^{Pos}_{i,t-1} + \beta_5 D^{MID}_{i,t-1} D^{Pos}_{i,t-1} + \beta_6 D^{HGH}_{i,t-1} D^{Pos}_{i,t-1}) Perf_{i,t-1} + Controls_{i,t-1} + \epsilon_{i,t}$$

(Eq. 7)

where $D^{MID}_{i,t-1}$ equals to 1 if fund *i* belongs to the three middle quintiles of Active Share from time period *t-1* to *t*, and 0 otherwise; $D^{HGH}_{i,t-1}$ equals to 1 if fund *i* belongs to the top quintile of Active Share from time period *t-1* to *t*, and 0 otherwise. These two dummy variables are used to capture the effect of belonging to a specific Active Share quintile on subsequent flows. More importantly, we include six other dummy variables which are Active Share quintiles interacting with past performance to capture the differential investors responses to good ($D^{Pos}_{i,t-1}$) and bad ($D^{Neg}_{i,t-1}$) past performance of mutual funds belonging to the bottom quintile, the three middle quintiles and the top quintile of Active Share. $Controls_{i,t-1}$ is the vector of control variables relating to fund characteristics as defined before, together with additional variables including fund family size, flows into fund family, and flows into fund segment. We also include time and segment fixed effect dummies and standard errors are clustered by fund.

This approach allows us to capture differential investor behavior in the positive and negative return domains, and provides a clearer explanation on estimated coefficients in terms of fund inflows and outflows. A positive coefficient on positive returns indicates investor inflows, whereas a positive coefficient on negative returns indicates investor outflows. Looking at the coefficients of the six interaction variables between past performance and Active Share in column (3) of Table 6, we can observe that, when experiencing positive past fund performance, one standard deviation increase of prior year risk adjusted performance leads to increases of 1.65%, 1.97%, 2.63% in cash inflows per quarter into mutual funds within the bottom, the three middle, and the top quintiles of Active Share, respectively. Differences in estimated coefficients between funds in the top quintile and funds in the bottom (middle) quintile of Active Share are statistically significant at the 5% (10%) level, indicating that investors are considerably more sensitive to good past performance if generated by funds with the highest Active Share.

On the other hand, when experiencing negative past fund performance, one standard deviation fall in prior year risk adjusted performance is associated with increases of 1.32% and 1.67% cash outflows per quarter to mutual funds within the bottom, and the three middle quintiles of Active Share. Surprisingly, however, cash outflows from funds within the top quintile of Active Share increase by just 1.37% for one standard deviation decrease in prior performance when the lagged performance is negative. Differences in estimated coefficients are not statistically significant at conventional levels, indicating that investors are similarly sensitive to bad performance across different levels of Active Share.[16]

These results are illustrated in Figure 5 which shows that in general investors invest disproportionately more in mutual funds with superior past performance but withdraw much less from funds that performed poorly. More interestingly, such asymmetric responses of investors to good and poor past performance are more pronounced among funds with high Active Share: there is no relative pronounced penalty for poor (negative) realized performance, but a marked bonus for high conviction managers from good (positive) realized returns. One possible explanation is that investors might interpret the good past performance of high conviction fund managers as signaling investment skill and consequently invest disproportionately more with them. In contrast, they might view poor past performance of such managers as the consequence of bad luck (ignoring the potential negative impact of their high conviction levels on fund returns). If this

[16] The results are robust to controlling for the potential observation dependence using Fama and MacBeth (1973) regressions. In all cases, we observe pronounced asymmetric investor responses to past performance of high Active Share funds relative to low Active Share funds.

is true, disproportionately higher inflows (lower outflows) after good (poor) past performance could act as additional confirming market signals for high conviction managers. This could then make them even more likely to attribute success to the strength of their conviction narratives but underperformance to external factors, thereby increasing their conviction levels even further. This is despite the evidence of our previous sub-section 4.2 which shows how high Active Share is associated with reduced returns and higher risk.

## 5. CONCLUSION

In this paper, we argue that conviction which is intrinsically emotionally determined and related to notions of belief and faith is the mechanism which enables professional investors to make investment decisions in a highly stressful and threatening environment where outcomes are inherently unpredictable, and skill cannot be distinguished from chance. Conviction trumps uncertainty and allows action. Specifically, we examine the performance implications of fund manager conviction levels as proxied by portfolio Active Share, the extent to which it deviates from its benchmark. Using a large sample of US mutual funds across three decades, we find that fund managers with outstanding prior performance are associated with significantly higher subsequent Active Share consistent with increased levels of conviction upon observing such investment 'success'. Such patterns are more pronounced among solo-managed funds which irrespectively manifest significantly higher conviction levels on average than team-managed funds. This is in line with the different psychological processes driving the behaviors of individuals and groups.

We also find strong evidence that high conviction is associated with both diminished future performance and increased fund risk. This finding could offer one potential explanation for the lack of performance persistence among successful fund managers. Specifically, too much conviction may lead to idiosyncratic and speculative investment decisions and too great a deviation from the respective benchmark index resulting in highly volatile returns and relative underperformance. Perhaps more interestingly, a closer look reveals a clear inverse U-shaped relationship between level of conviction and subsequent performance; underconviction, i.e., 'benchmark hugging' or 'closet indexing', similarly leads to underperfomance after costs.

In addition, we shed new light on the determinants of fund flows by examining how investors respond to high conviction fund managers. Our results suggest that investors chase high conviction, flocking to funds with high Active Share when observing good past fund performance but failing to flee from these funds to the same extent following poor performance. We wonder if such asymmetric reactions of fund clients could adversely impact the performance of high conviction fund managers who might rashly increase their conviction level even further viewing increased fund inflows as confirming market signals of their investment ability.

In future work investigating the impact of conviction on subsequent fund performance and fund flows, researchers can explore other conviction proxies including portfolio turnover, portfolio concentration, and idiosyncratic risk exposure. Another area for further research relates to the demographic factors which might influence fund manager conviction including educational background, past experience, location, and gender.

Based on what we have found, we speculate that the lack of evidence of superior fund performance in the literature could be partially attributable to overconviction among fund managers and the associated denial, both conscious and probably more unconscious, of the fact that investment outcomes are outside their control. What is unrealistically expected of the professional asset manager is very difficult if not impossible to deliver except by chance cannot be directly acknowledged either by their clients or by the fund managers themselves.

The key role emotions play in all fund management activity is an underexplored area in empirical investment research. We believe the complementary emotional dimensions of the asset manager's task need to be more formally addressed in future studies which could lead to important new insights and a richer understanding of the decision processes of real-world fund managers and their associated investment performance.

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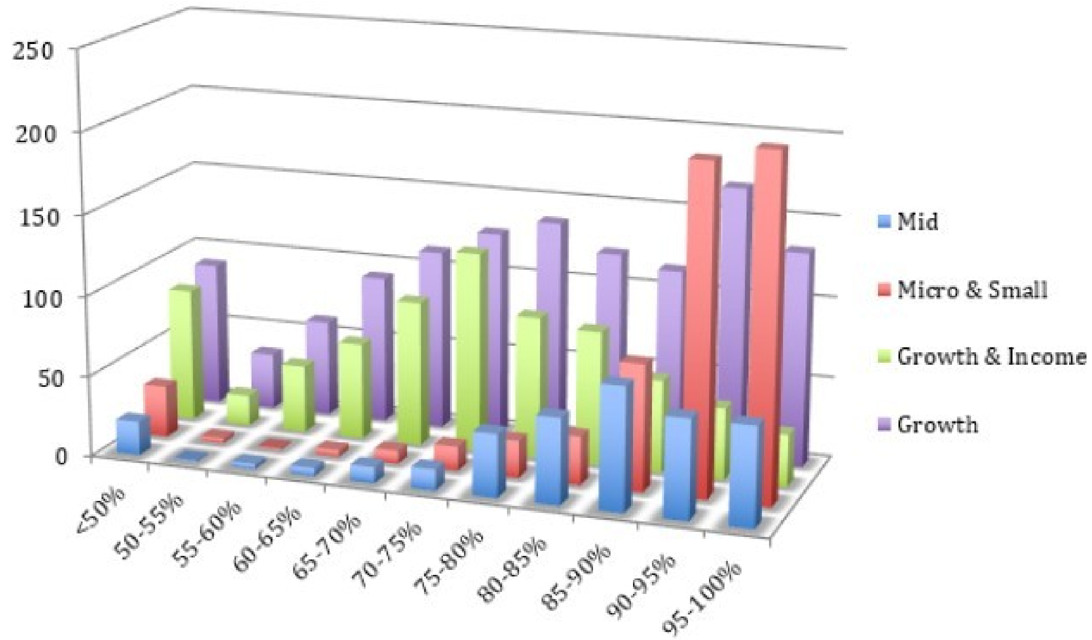
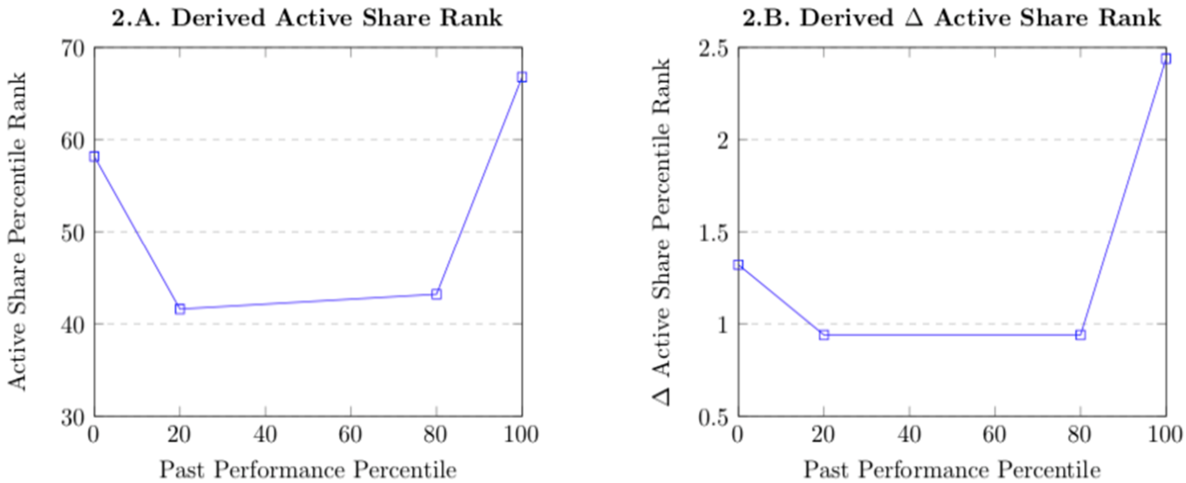
**Figure 1. Number of Mutual Funds by Active Share Category and Fund Style**

The figure below shows the number of mutual funds in each time series average of Active Share category across four major CRSP investment objective segments including Micro-cap and Small-cap funds, Mid-cap funds, Growth funds, and Growth and Income funds. Our mutual funds are grouped into these four major segments due to the small number of cases for Micro-cap and Income funds.



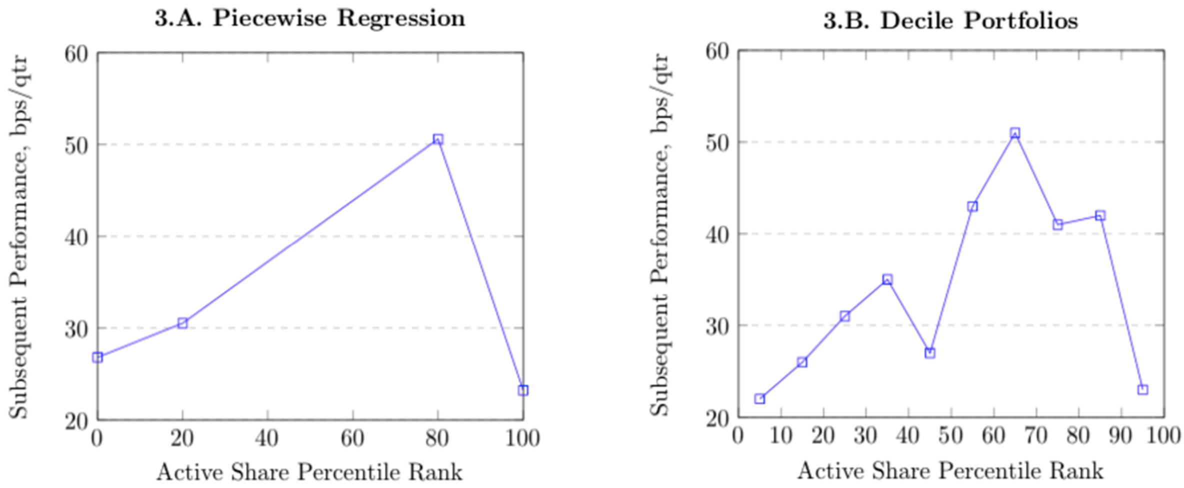
## Figure 2. Fund Past Performance and Active Share

Figure 2.A. shows the estimated non-linear relationship between a fund's past performance rank and its current Active Share rank based on the results from the piecewise regression model specification (3) in Table 2. Figure 2.B. shows the estimated non-linear relationship between a fund's past performance percentile rank and its change in Active Share rank over the quarter based on the results from the piecewise regression model specification (6) in Table 2. Past Fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter t and past performance rank that is measured as the percentile normalized rank of estimated past performance relative to other funds in the same market segment.



## Figure 3. Active Share and Future Fund Performance

Figure 3.A. shows the estimated non-linear relationship between a fund's Active Share relative to other funds in the same segment and its future performance, based on the results from the piecewise regression model specification (3) in Table 4. Figure 3.B. shows the estimated subsequent performance of Active Share rank portfolios by decile. Active Share rank is measured as the normalized percentile rank of a fund's Active Share relative to other funds in the same market segment. Fund performance is measured by its Carhart (1997) four-factor abnormal return estimated using past 12 monthly return data.



## Figure 4. Active Share and Fund Risk

Figure 4.A. shows the estimated non-linear relationship between a fund's Active Share relative to other funds in the same segment and subsequent performance extremity, based on the results from the piecewise regression model specification (3) in Table 5. Following Bär et al. (2011), performance extremity is calculated as the absolute difference between a fund's performance and the average performance of all funds in the same market segment. Fund performance is measured by its Carhart (1997) four-factor abnormal return estimated using past 12 monthly return data. Figure 4.B. shows the estimated relationship between a fund's Active Share rank and return dispersion, based on the results from model specification (7) in Table 5. Performance dispersion is the standard deviations of residuals from the Carhart (1997) four-factor model. Active Share percentile rank is measured as the normalized rank of a fund's Active Share relative to other funds in the same market segment.

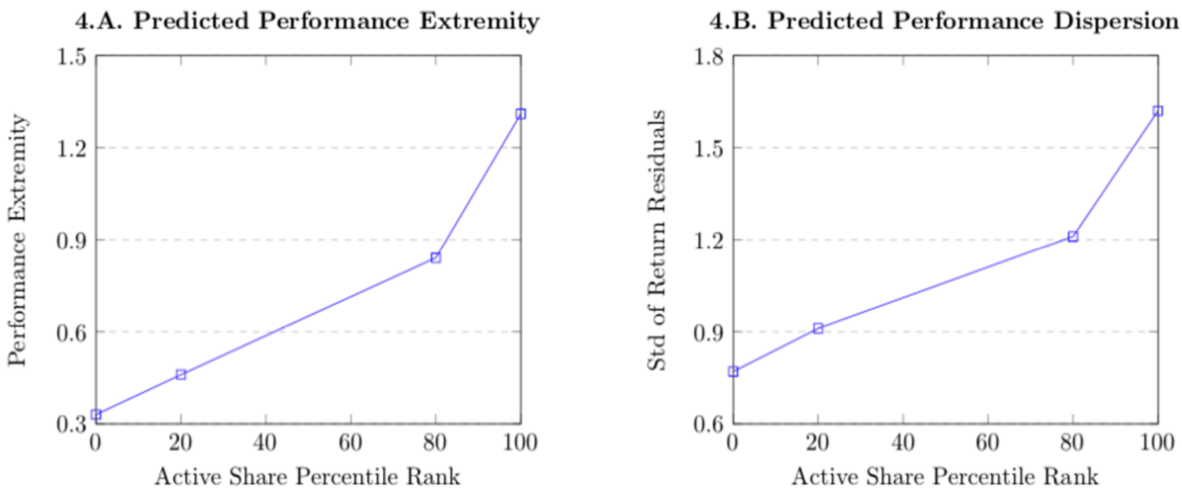
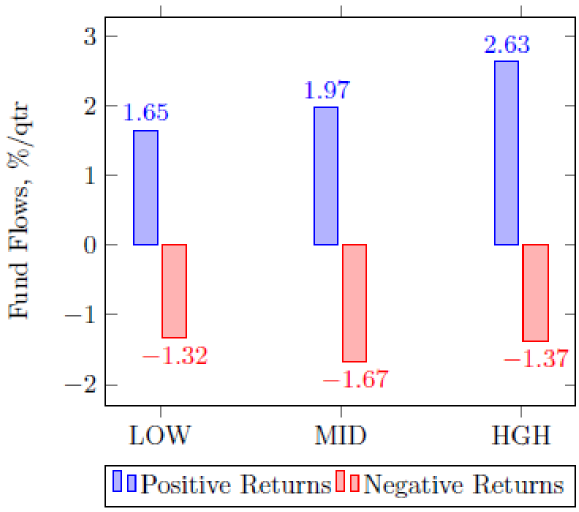


**Figure 5. Fund Performance, Active Share, and Investor Flows**

The figure below shows differential investors responses to good (positive) and bad (negative) past performance of mutual funds belonging to the bottom quintile (LOW), the three middle quintiles (MID) and the top quintile (HGH) of Active Share, based on the results from model specification (3) in Table 6. Magnitudes of the fund inflows (outflows) shown in the figure are for one standard deviation increase (decrease) in fund past performance when fund returns are positive (negative). Fund past performance is the estimated alpha based on the Carhart (1997) four-factor model over the one-year period prior to the current quarter t. Active Share rank is measured as the normalized rank of a fund's Active Share relative to other funds in the same market segment.



## Table 1. Descriptive Statistics

This table reports the summary statistics of a total of 2740 unique US domestic equity mutual fund samples from 1980 to 2009. The mutual fund data with self-reporting investment objectives including Growth, Growth & Income, Income, Micro-Cap, Small-Cap, and Mid-Cap are obtained from the merged CRSP mutual fund holdings databases and CRSP mutual fund characteristics databases in CRSP Survivor-Bias-Free US Database. CRSP investment objective variable (crsp_obj_cd) is used to filter US domestic equity mutual funds from the CRSP mutual funds universe in CRSP mutual fund database. The mutual funds are broken down by the CRSP investment objectives, including growth, growth & income, income, micro-cap, small-cap, and mid-cap. The number of funds is the total number of unique mutual funds that exist during the sample periods. Average (Median) Assets is the average (Median) of total net assets under management of mutual funds in million dollars. Average Expense is cross-sectional average expense ratio of mutual funds. Average Turnover is the cross-sectional average of mutual fund turnover ratio. Average Active Share is the cross-sectional average Active Share of mutual funds and SD of Active Share is the cross-sectional standard deviation of Active Share of mutual funds. Active Share is calculated as the one half of the sum of absolute deviations in portfolio weight of a fund portfolio from its benchmark index portfolio. Panel A reports the statistics of all mutual fund samples over time and Panel B reports the statistics of mutual fund with different investment objectives.

| | **Number of Funds** | **Average Assets** | **Median Assets** | **Average Expense** | **Average Turnover** | **Average Active Share** | **SD Active Share** |
|---|---|---|---|---|---|---|---|
| *Panel A: Descriptive Statistics by Year* | | | | | | | |
| **1980** | 105 | 195.05 | 72.90 | 0.98% | 82.91% | 90.55% | 11.41% |
| **1985** | 159 | 323.50 | 150.97 | 1.03% | 80.79% | 90.53% | 10.33% |
| **1990** | 323 | 460.69 | 460.69 | 1.20% | 81.18% | 81.69% | 14.97% |
| **1995** | 794 | 931.49 | 212.59 | 1.20% | 81.42% | 78.72% | 20.15% |
| **2000** | 1354 | 1465.24 | 250.25 | 1.24% | 97.95% | 72.06% | 24.39% |
| **2005** | 1540 | 1549.72 | 252.05 | 1.26% | 82.87% | 74.97% | 22.99% |
| **2009** | 1287 | 1591.50 | 278.40 | 1.18% | 94.60% | 74.01% | 22.87% |
| *Panel B: Descriptive Statistics by Style* | | | | | | | |
| **Micro-Cap** | 38 | 304.01 | 131.80 | 1.62% | 108.62% | 95.12% | 6.03% |
| **Small-Cap** | 592 | 653.49 | 213.42 | 1.32% | 98.95% | 84.83% | 20.00% |
| **Mid-Cap** | 342 | 845.69 | 219.90 | 1.26% | 115.20% | 78.28% | 21.89% |
| **Growth** | 1296 | 1296.47 | 195.92 | 1.21% | 88.61% | 75.57% | 17.79% |
| **Growth & Income** | 612 | 1957.11 | 263.31 | 1.11% | 64.86% | 67.45% | 19.64% |
| **Income** | 126 | 1625.05 | 284.10 | 1.17% | 57.52% | 71.29% | 23.83% |

## Table 2. Past Performance and Active Share

The dependent variable, Active Share, for model specifications (1) to (3) is the normalized rank of Active Share relative to other funds in the same market segment, for each fund-quarter observation. For model specifications (4) to (6), the dependent variable Δ Active Share is changes in the normalized rank of Active Share over each quarter. Perf is the normalized rank of relative fund past performance. Fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. $\text{Perf}^{\text{LOW}}$ represents the bottom quintile of past performance rank that is measured as the normalized rank of fund past performance relative to other funds in the same market segment. $\text{Perf}^{\text{MID}}$ represents the three middle quintiles and $\text{Perf}^{\text{HGH}}$ represents the top quintile of past performance rank. To mitigate potential endogeneity problems, this paper lags all other control variables by one quarter, except the expenses ratio and turnover ratio which are lagged one year due to data availability. Control variables include: fund age is measured as the natural logarithm of age in years since first offer date; fund size is the natural logarithm of total net assets under management in millions of dollars; expense ratio and turnover ratio are measured in percent; tenure is calculated as the natural logarithm of current manager tenure in years; fund flow is estimated by the ratio of $\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \cdot (1 + \text{RET}_{i,t}) - \text{MGR}_{i,t}$ to $\text{TNA}_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorizes the fund flow and turnover ratios at the 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control for segment fixed effect. The data are quarterly and cover the 1993-2009 period. t-statistics (in parentheses) are based on standard errors clustered by fund. Significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

| | **Active Share** | | | **Δ Active Share** | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Perf | 0.069*** | -0.757*** | | 0.005*** | -0.031*** | |
| | (8.91) | (-22.61) | | (4.15) | (-4.74) | |
| $\text{Perf}^2$ | | 0.823*** | | | 0.037*** | |
| | | (24.92) | | | (5.90) | |
| $\text{Perf}^{\text{LOW}}$ | | | -0.851*** | | | -0.019 |
| | | | (-16.10) | | | (-1.60) |
| $\text{Perf}^{\text{MID}}$ | | | 0.045*** | | | -0.000 |
| | | | (4.12) | | | (-0.03) |
| $\text{Perf}^{\text{HGH}}$ | | | 1.132*** | | | 0.075*** |
| | | | (22.54) | | | (7.16) |
| Fund Controls | Y | Y | Y | Y | Y | Y |
| Style Controls | Y | Y | Y | Y | Y | Y |
| Time Effects | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.134 | 0.179 | 0.180 | 0.034 | 0.035 | 0.036 |
| Observations | 45345 | 45345 | 45345 | 43675 | 43675 | 43675 |

## Table 3. Past Performance and Active Share, Solo vs Team

The dependent variable, Active Share, for the model specification (1) is the normalized rank of Active Share relative to other funds in the same market segment, for each fund-quarter observation. For the model specification (2), the dependent variable $\Delta$ Active Share is changes in the normalized rank of Active Share over each quarter. $D_{solo}$ equals to 1 if mutual fund *i* is managed by a single manager during the period *t-1* to *t*, and 0 otherwise. Fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. $Perf^{LOW}$ represents the bottom quintile of past performance rank that is measured as the normalized rank of fund past performance relative to other funds in the same market segment. $Perf^{MID}$ represents the three middle quintiles and $Perf^{HGH}$ represents the top quintile of past performance rank. To mitigate potential endogeneity problems, this paper lags all other control variables by one quarter, except the expenses ratio and turnover ratio which are lagged one year due to data availability. Control variables include: fund age is measured as the natural logarithm of age in years since first offer date; fund size is the natural logarithm of total net assets under management in millions of dollars; expense ratio and turnover ratio are measured in percent; tenure is calculated as the natural logarithm of current manager tenure in years; fund flow is estimated by the ratio of $TNA_{i,t} - TNA_{i,t-1} \cdot (1 + RET_{i,t}) - MGR_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorizes fund flow and the turnover ratios at the 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control for segment fixed effect. t-statistics (in parentheses) are based on standard errors clustered at fund level.

| | **Active Share** | **$\Delta$ Active Share** |
|---|---|---|
| | (1) | (2) |
| $D_{solo}$ | 0.046*** | 0.008* |
| | (3.55) | (1.70) |
| $D_{solo} * Perf^{LOW}$ | -0.276*** | -0.037 |
| | (-3.48) | (-1.50) |
| $D_{solo} * Perf^{MID}$ | -0.026 | -0.004 |
| | (-1.59) | (-0.83) |
| $D_{solo} * Perf^{HGH}$ | 0.129* | 0.036* |
| | (1.87) | (1.86) |
| $Perf^{LOW}$ | -0.627*** | 0.033 |
| | (-8.05) | (1.20) |
| $Perf^{MID}$ | 0.063*** | 0.001 |
| | (3.56) | (0.28) |
| $Perf^{HGH}$ | 0.981*** | 0.041** |
| | (13.59) | (2.41) |
| Fund Controls | Y | Y |
| Style Controls | Y | Y |
| Time Effects | Y | Y |
| $R^2$ | 0.214 | 0.093 |
| Observations | 40009 | 40009 |

## Table 4. Active Share and Future Fund Performance

The dependent variable is abnormal returns estimated using past monthly fund returns based on the Carhart (1997) four-factor model. Active Share represents the normalized rank of Active Share relative to other funds in the same market segment. Active Share$^{LOW}$ represents the bottom quintile of Active Share measured as the normalized rank of fund Active Share relative to other funds in the same market segment. Active Share$^{MID}$ represents the three middle quintiles and Active Share$^{HGH}$ represents the top quintile of Active Share rank. $\Delta$ Active Share represents changes in relative Active Share over the quarter. To mitigate potential endogeneity problems, this paper lags all other control variables by one quarter, except the expenses ratio and turnover ratio which are lagged one year due to data availability. Control variables include: fund age is measured as the natural logarithm of age in years since first offer date; fund size is the natural logarithm of total net assets under management in millions of dollars; expense ratio and turnover ratio are measured in percent; tenure is calculated as the natural logarithm of current manager tenure in years; fund flow is estimated by the ratio of $\mathrm{TNA}_{i,t} - \mathrm{TNA}_{i,t-1} \cdot (1 + \mathrm{RET}_{i,t}) - \mathrm{MGR}_{i,t}$ to $\mathrm{TNA}_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorizes the fund flow and turnover ratios at the 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control for segment fixed effect. t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Active Share | 0.0012 | 0.0079*** | | |
| | (1.64) | (2.70) | | |
| Active Share$^2$ | | -0.0065** | | |
| | | (-2.14) | | |
| Active Share$^{LOW}$ | | | 0.0030 | |
| | | | (0.67) | |
| Active Share$^{MID}$ | | | 0.0031** | |
| | | | (2.41) | |
| Active Share$^{HGH}$ | | | -0.0137** | |
| | | | (-2.01) | |
| $\Delta$ Active Share | | | | -0.0093*** |
| | | | | (-2.64) |
| Fund Controls | Y | Y | Y | Y |
| Style Controls | Y | Y | Y | Y |
| Time Effects | Y | Y | Y | Y |
| $R^2$ | 0.040 | 0.038 | 0.040 | 0.039 |
| Observations | 45345 | 43388 | 42265 | 42757 |

## Table 5. Active Share and Fund Risk

The dependent variable is the absolute difference between a fund's performance and the average performance of all funds in the same market segment. Fund future performance is estimated using past monthly returns based on the Carhart (1997) four-factor model. Active Share represents the normalized rank of Active Share relative to other funds in the same market segment. Active $\text{Share}^{LOW}$ represents the bottom quintile of Active Share measured as the normalized rank of fund Active Share relative to other funds in the same market segment. Active $\text{Share}^{MID}$ represents the three middle quintiles and Active $\text{Share}^{HGH}$ represents the top quintile of Active Share rank. Δ Active Share represents changes in relative Active Share over the quarter. To mitigate potential endogeneity problems, this paper lags all other control variables by one quarter, except the expenses ratio and turnover ratio which are lagged one year due to data availability. Control variables include: fund age is measured as the natural logarithm of age in years since first offer date; fund size is the natural logarithm of total net assets under management in millions of dollars; expense ratio and turnover ratio are measured in percent; tenure is calculated as the natural logarithm of current manager tenure in years; fund flow is estimated by the ratio of $\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \cdot (1 + \text{RET}_{i,t}) - \text{MGR}_{i,t}$ to $\text{TNA}_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorizes fund flow and turnover ratios at the 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control for segment fixed effect. t-statistics (in parentheses) are based on standard errors clustered by fund.

| | **Performance Extremity** | | | | **Performance Dispersion** | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Active Share | 0.8099*** | 0.1816* | | | 0.0070*** | 0.0020*** | | |
| | (27.09) | (1.91) | | | (25.91) | (1.91) | | |
| Active $\text{Share}^2$ | | 0.6378*** | | | | 0.0049*** | | |
| | | (6.31) | | | | (4.79) | | |
| Active $\text{Share}^{LOW}$ | | | 0.7123*** | | | | 0.0071*** | |
| | | | (4.02) | | | | (4.50) | |
| Active $\text{Share}^{MID}$ | | | 0.6208*** | | | | 0.0053*** | |
| | | | (15.58) | | | | (15.19) | |
| Active $\text{Share}^{HGH}$ | | | 2.2675*** | | | | 0.0189*** | |
| | | | (9.32) | | | | (9.14) | |
| Δ Active Share | | | | 0.1099* | | | | 0.0051*** |
| | | | | (1.85) | | | | (7.03) |
| Fund Controls | Y | Y | Y | Y | Y | Y | Y | Y |
| Style Controls | Y | Y | Y | Y | Y | Y | Y | Y |
| Time Effects | Y | Y | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.075 | 0.079 | 0.080 | 0.077 | 0.225 | 0.226 | 0.227 | 0.187 |
| Observations | 45345 | 43388 | 43388 | 43372 | 43388 | 43388 | 43388 | 42434 |

## Table 6. Active Share and Fund Flows

The dependent variable is quarterly fund flows in percent, estimated by the ratio of $\mathbf{TNA_{i,t} - TNA_{i,t-1} \cdot (1 + RET_{i,t}) - MGR_{i,t}}$ to $\mathbf{TNA_{i,t-1}}$. Active Share is measured as the normalized rank of fund Active Share relative to other funds in the same market segment. $\boldsymbol{D^{MID}_{Active\ Share}}$ equals to 1 if fund *i* belongs to the three middle quintiles of Active Share rank, 0 otherwise. $\boldsymbol{D^{HGH}_{Active\ Share}}$ equals to 1 if fund *i* belongs to the top quintile of Active Share rank, 0 otherwise. $\boldsymbol{D^{Neg}_{Perf}}$ equals to 1 if fund *i* has negative past performance, 0 otherwise. $\boldsymbol{D^{Pos}_{Perf}}$ equals to 1 if fund *i* has positive past performance, 0 otherwise. Fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. To mitigate potential endogeneity problems, this paper lags all other control variables by one quarter, except the expenses and turnover ratios which are lagged one year due to data availability. Control variables include: fund age is measured as the natural logarithm of age in years since first offer date; fund size is the natural logarithm of total net assets under management in millions of dollars; family size is calculated as the natural logarithm of total net assets under management of the fund complex that the fund belongs to; expense ratio and turnover ratio are measured in percent; tenure is calculated as the natural logarithm of current manager tenure in years; in addition, family flow and market segment flow are the percentage flows to a fund's family and the market segment, respectively. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorizes fund flow and turnover ratios at the 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control for segment fixed effect. t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| Active Share | 0.0165*** | | |
| | (8.24) | | |
| $D^{MID}_{Active\ Share}$ | | 0.0011 | 0.0011 |
| | | (0.90) | (0.53) |
| $D^{HGH}_{Active\ Share}$ | | 0.0132*** | 0.0077** |
| | | (7.32) | (2.61) |
| $D^{LOW}_{Active\ Share} * D^{Neg}_{Perf} * Perf$ | | | 1.8894*** |
| | | | (5.17) |
| $D^{MID}_{Active\ Share} * D^{Neg}_{Perf} * Perf$ | | | 2.3889*** |
| | | | (13.87) |
| $D^{HGH}_{Active\ Share} * D^{Neg}_{Perf} * Perf$ | | | 1.9620*** |
| | | | (7.69) |
| $D^{LOW}_{Active\ Share} * D^{Pos}_{Perf} * Perf$ | | | 2.3503*** |
| | | | (4.92) |
| $D^{MID}_{Active\ Share} * D^{Pos}_{Perf} * Perf$ | | | 2.8278*** |
| | | | (8.32) |
| $D^{HGH}_{Active\ Share} * D^{Pos}_{Perf} * Perf$ | | | 3.7620*** |
| | | | (7.50) |
| Fund Controls | Y | Y | Y |
| Family Controls | Y | Y | Y |
| Segment Controls | Y | Y | Y |
| Time Effects | Y | Y | Y |
| $R^2$ | 0.284 | 0.290 | 0.311 |
| Observations | 49410 | 50602 | 50602 |

# Appendix

## Table A1. Past Performance and Active Share (2010-2018)

The dependent variable, Active Share, for model specifications (1) to (3) is the normalized rank of Active Share relative to other funds in the same market segment, for each fund-quarter observation. For model specifications (4) to (6), the dependent variable $\Delta$ Active Share is changes in the normalized rank of Active Share over each quarter. Perf is the normalized rank of relative fund past performance. Fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. $\text{Perf}^{\text{LOW}}$ represents the bottom quintile of past performance rank that is measured as the normalized rank of fund past performance relative to other funds in the same market segment. $\text{Perf}^{\text{MID}}$ represents the three middle quintiles and $\text{Perf}^{\text{HGH}}$ represents the top quintile of past performance rank. To mitigate potential endogeneity problems, this paper lags all other control variables by one quarter, except the expenses ratio and turnover ratio which are lagged one year due to data availability. Control variables include: fund age is measured as the natural logarithm of age in years since first offer date; fund size is the natural logarithm of total net assets under management in millions of dollars; expense ratio and turnover ratio are measured in percent; tenure is calculated as the natural logarithm of current manager tenure in years; fund flow is estimated by the ratio of $\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \cdot (1 + \text{RET}_{i,t}) - \text{MGR}_{i,t}$ to $\text{TNA}_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorizes the fund flow and turnover ratios at the 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control for segment fixed effect. The data are quarterly and cover the 2010-2018 period. t-statistics (in parentheses) are based on standard errors clustered by fund. Significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

| | **Active Share** | | | **$\Delta$ Active Share** | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Perf | 0.0033* | -0.0133* | | 0.0025* | -0.0086* | |
| | (1.66) | (-1.57) | | (1.79) | (-1.65) | |
| $\text{Perf}^2$ | | 0.0154** | | | 0.0109* | |
| | | (1.97) | | | (1.80) | |
| $\text{Perf}^{\text{LOW}}$ | | | -0.0319** | | | -0.0208* |
| | | | (-1.97) | | | (-1.88) |
| $\text{Perf}^{\text{MID}}$ | | | 0.0067** | | | 0.0058*** |
| | | | (2.11) | | | (2.74) |
| $\text{Perf}^{\text{HGH}}$ | | | 0.0263* | | | 0.0260*** |
| | | | (1.84) | | | (2.72) |
| Fund Controls | Y | Y | Y | Y | Y | Y |
| Style Controls | Y | Y | Y | Y | Y | Y |
| Time Effects | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.045 | 0.045 | 0.022 | 0.079 | 0.084 | 0.080 |
| Observations | 15439 | 15439 | 15439 | 14152 | 14152 | 14152 |

## Table A2. Active Share and Future Fund Performance (2010-2018)

The dependent variable is abnormal returns estimated using past monthly fund returns based on the Carhart (1997) four-factor model. Active Share represents the normalized rank of Active Share relative to other funds in the same market segment. $\text{Active Share}^{LOW}$ represents the bottom quintile of Active Share measured as the normalized rank of fund Active Share relative to other funds in the same market segment. $\text{Active Share}^{MID}$ represents the three middle quintiles and $\text{Active Share}^{HGH}$ represents the top quintile of Active Share rank. Δ Active Share represents changes in relative Active Share over the quarter. To mitigate potential endogeneity problems, this paper lags all other control variables by one quarter, except the expenses ratio and turnover ratio which are lagged one year due to data availability. Control variables include: fund age is measured as the natural logarithm of age in years since first offer date; fund size is the natural logarithm of total net assets under management in millions of dollars; expense ratio and turnover ratio are measured in percent; tenure is calculated as the natural logarithm of current manager tenure in years; fund flow is estimated by the ratio of $\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \cdot (1 + \text{RET}_{i,t}) - \text{MGR}_{i,t}$ to $\text{TNA}_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorizes the fund flow and turnover ratios at the 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control for segment fixed effect. The data are quarterly and cover the 2010-2018 period. t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Active Share | 0.0019 | 0.0331** | | |
| | (0.38) | (2.03) | | |
| $\text{Active Share}^2$ | | -0.0584** | | |
| | | (-2.11) | | |
| $\text{Active Share}^{LOW}$ | | | 0.0037 | |
| | | | (0.24) | |
| $\text{Active Share}^{MID}$ | | | 0.0163** | |
| | | | (2.26) | |
| $\text{Active Share}^{HGH}$ | | | -0.1690* | |
| | | | (-1.76) | |
| Δ Active Share | | | | -0.0085* |
| | | | | (-1.67) |
| Fund Controls | Y | Y | Y | Y |
| Style Controls | Y | Y | Y | Y |
| Time Effects | Y | Y | Y | Y |
| $R^2$ | 0.069 | 0.070 | 0.080 | 0.085 |
| Observations | 15364 | 15364 | 14145 | 13445 |