# Fund Manager Active Share, Overconfidence and Investment Performance


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## ABSTRACT

This paper studies overconfidence among equity mutual fund managers using a sample of 2740 unique funds during the 1980-2009 period. Using *Active Share* - the sum of absolute deviations from the benchmark index - as a proxy for the conviction level of professional investors, we show that fund managers tend to boost their confidence following superior past performance, and that the bias is more pronounced among solo-managed funds compared to team-managed funds. More importantly, we illustrate an inverted-U relationship between the fund manager's confidence level and his or her subsequent investment performance. In particular, excessive confidence is associated with diminished future returns, more extreme performance outcomes, and higher dispersion. We further document an irrational investor reaction to fund manager overconfidence. This comes in the form of higher net inflows as a reward for good performance of overconfident managers but no pronounced penalty for poor performance *ceteris paribus*.



*Keywords: Equity investing, Behavioral biases, Mutual funds, Fund performance, Fund flows*


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# Fund Manager Active Share, Overconfidence, and Investment Performance

## 1. Introduction

A considerable body of research on fund management focuses on whether fund managers have specific skills, whether particular investment strategies generate superior returns, and testing market efficiency. In comparison, much less work has been done on the psychology of fund managers and the impact of behavioral biases such as overconfidence on their performance. The role of overconfidence in influencing the behaviour of economic agents and, by extension, the functioning of financial markets, is an important research topic (e.g., Daniel, Hirshleifer and Subrahmanyam, 1998; Santos-Pinto and Sobel, 2005; Statman, Thorley and Vorkink, 2006; and Garcia, Sangiorgi and Urošević, 2007). It has even been suggested that no problem in judgment and decision-making is “more prevalent and more potentially catastrophic than overconfidence” (Plous, 1993). Overconfidence has been cited as an explanation for wars, strikes, litigations, entrepreneurial failures and, not surprisingly, stock market bubbles (Glaser, Noth and Weber, 2007; Moore and Healy, 2008). A large body of literature has recently focused on the overconfidence of corporate managers, and its impact on corporate investment decisions in areas such as capital structure and M&A activity (see Malmendier and Tate, 2005; Malmendier and Tate, 2008; Malmendier, Tate and Yan, 2011; and Gervais, Heaton and Odean, 2011 among others).

The lack of research on overconfidence of professional investors is therefore surprising. In this paper, we use the sum of absolute deviations from the fund’s benchmark index (i.e., *Active Share*) as a proxy for confidence, and examines the potential relationship between investment performance and managerial confidence. By analyzing a large sample of US domestic actively managed equity mutual funds, we find a clear U-shaped relationship between past performance of funds and their subsequent Active Share level. In particular, we find robust evidence that fund managers become overconfident after experiencing outstanding performance, as reflected by the considerably high Active Share level of their portfolios in the subsequent period. Interestingly, fund managers suffering poor past performance are also more likely to increase their Active Share in the subsequent period. What can possibly explain this is the tendency of poorly performing managers in engaging in gambling to increase the chance of catching up their positions in the future. Consistently, we observe that fund managers are more likely to increase their Active Share levels following good performance. Overall, these results strongly support our main hypothesis that good performance leads to overconfidence which eventually leads to a higher Active Share. Like retail investors, fund managers seem to falsely attribute good past performance to their own skills. This effect is more pronounced among solo-managed funds.

More importantly, our paper directly examines the potential impact of fund manager overconfidence on subsequent fund performance. Our results show that excessive overconfidence as measured by extremely high Active Share relative to all other funds in the same segment is significantly associated with diminished future performance. Interestingly, we also find that fund managers with normal confidence levels as reflected by moderate Active Share level deliver superior performance. We argue that moderate Active Share levels might better reflect managers' normal levels of confidence and less biased investment decisions. The evidence is consistent with fund managers with 'normal' confidence levels assessing and updating the precision of their private information in a more rational way. Consequently, it might be rational for them to put larger weights on their private information and smaller weights on other stocks from their benchmark indices. These well motivated trading activities appear empirically to lead to the realization of profitable opportunities and better portfolio allocation, which eventually generates better performance. Overall, an inverted U-shaped relationship between confidence level of fund managers and their subsequent performance is revealed.

Further, we find a negative and significant relationship between changes in Active Share rank and subsequent performance, which is consistent with our main conjecture that excessive overconfidence is associated with deteriorated subsequent returns. Additionally, our results show a clear convex relation between confidence level and fund risk including performance extremity and performance dispersion, suggesting that excessive overconfidence is associated with more extreme outcome, higher performance dispersion, and therefore a potentially higher downside risk.

We also shed new light on the determinants of fund flows in the context of investor response to fund manager overconfidence. The results are striking. When past performance is positive, we observe significantly higher fund inflows to overconfident managers with an extremely high Active Share than other funds, while fund outflows from mutual funds with overconfident managers are not significantly larger than other funds when past performance is negative. This indicates that, for overconfident fund managers, there is a marked bonus for good performance while there is no pronounced penalty for their poor performance comparing to other funds. One possible explanation for these responses is that, upon observing good fund performance, investors might falsely attribute successes to managers' investment skills rather than luck while attribute their failure to chance. In particular, extreme high Active Share due to fund manager overconfidence, can easily be misunderstood by investors as an indicator of fund manager skill. As a consequence, investors chase overconfident fund managers, flocking to funds with extremely high Active Share following good performance but failing to flee from these to the same extent following poor performance.

Our paper contributes to three strands of finance literature. *Firstly*, our findings contribute to the literature on behavioral biases and heuristics among professional investors. While overconfidence has been extensively documented among retail investors and corporate executives, evidence on professional investors is scarce. Few recent papers provide empirical evidence as we do showing that professional investors such as mutual fund managers are subject to self-serving attribution bias and overconfidence. Puetz and Puenz (2011) report that fund managers trade more excessively after good performance. A working paper by Choi and Lou (2010) uses Active Share as a proxy of overconfidence and use the sum of positive (negative) past performance as a proxy for confirming (disconfirming) market signals. They find evidence showing that fund managers tend to boost their confidence to a larger extent after confirming market signals than to decrease confidence after disconfirming market signals. Eshraghi and Taffler (2014) apply content analysis on the reports managers write to their investors and show mutual fund managers who generate superior past performance become overconfident. Additionally, our paper contributes to the literature by highlighting significant behavioral differences between solo- and team-managed funds. The extant literature mainly focuses on overall performance (Prather and Middleton, 2002, 2006; Chen et al 2004) and Massa, Reuter, and Zitzewitz (2010) focus on the strategic decision of fund houses to disclose the names of fund management teams and the subsequent investor reaction.

*Secondly*, this paper contributes to the literature on determinants of mutual fund performance. Despite the extensive literature examining overconfidence and the potential impact of overconfidence among retail investors and corporate managers, few studies directly examine at the role of confidence on subsequent performance. This paper is one of the first attempts to explore the potential non-linear relationship between confidence level and future performance.

*Thirdly*, our paper contributes to the literature on mutual fund flows. Many investors chase funds with superior past performance but fail to flee from poorly performing funds (e.g., Sirri and Tufano, 1998 and among others). Investors are also sensitive to fund expenses and management fees (Sirri and Tufano, 1998; Barber, Odean, and Zhang, 2005) and other documented determinants of fund flows including fund advertising (Jain and Wu, 2000; Gallaher, Kaniel, and Starks, 2008), media coverage (Kaniel, Starks, and Vasudevan, 2007), fund attribute (Bollen, 2007), and fund manager characteristics (e.g., Wermers, 2003; Niessen-Ruenzi and Ruenzi, 2013; Kumar, Niessen-Ruenzi, and Spalt, 2015). This paper contributes to this literature by showing for the first time that managerial overconfidence has a significant impact on mutual fund flows. Investors appear to irrationally chase overconfident managers.

The remainder of this paper is organized as follows. In Section 2, the paper reviews recent related literature on overconfidence. Section 3 discusses motivation and develops the main research questions. Section 4 describes the related methodology used in this paper. Section 5 presents data source and sample construction. Section 6 shows the empirical analysis and results and Section 7 concludes.

## 2. Literature Review

Traditional finance seeks to understand financial market by predominately assuming economic agents are perfectly "rational" in theoretical models. Under this assumption, these agents process information correctly and make decisions in an unbiased way to constantly maximize their utility. However, it has become clear now that this appealingly simple approach fails to explain asset pricing anomalies and individual trading behaviors found in the empirical studies (e.g., Barberis and Thaler, 2003). Behavioral finance suggests that human beings are not fully "rational" and are subject to behavioral bias and heuristics that can potentially affect their information processing and decision making. In particular, overconfidence is one of the most recognized and documented behavioral attributes in the psychological literature. The majority of studies in the finance literature relates managerial overconfidence to decision-making in the context of corporate finance, showing that corporate managers who are subject to overconfidence bias tend to make value-destroying investment, merger and acquisition, and financing decisions (e.g., Malmendier and Tate, 2005, 2008; Malmendier, Tate, and Yan, 2011; and Gervais, Heaton and Odean, 2011).

The literature also seeks to investigate the potential impact of overconfidence on investors' investment decisions and trading behaviors in the financial market. Indeed, there is ample evidence showing that retail investors are prone to overconfidence bias. For example, recent studies document that individual investors trade too much and such excessive trading eventually leads to negative returns net of transaction costs (e.g., Odean, 1999; Barber and Odean, 2000, 2001, 2002; Grinblatt and Keloharju, 2009).

Gervais and Odean (2001) seeks to understand and explain overconfidence in a dynamic context by the self-serving attribution bias which is a well-established behavioral bias in the psychological literature. This bias states that people tend to attribute good (positive) outcome to their own skills while they blame poor (negative) outcome to chance (e.g., Hastorf, Schneider, and Polefka 1970; Miller and Ross, 1975). In a financial context, Gervais and Odean (2001) argue that investors learn their own ability from their past successes and failures and self-serving attribution bias leads them to take too much credit for their good outcomes but too little responsibility for poor outcomes and eventually leads them to become overconfident. In financial markets where the unobserved quality of investors' private information can only be learned through delayed and noisy feedbacks, they are particularly susceptible to the self-serving attribution bias and therefore prone to overconfidence.

The nature of professional experience in asset management can easily expose fund managers to the risk of becoming overconfident: fund managers are constantly under intensive competition to outperform their peers who are equally qualified; they are swamped with incomplete information that is often conflicting and open to competing interpretations (Tuckett and Taffler, 2012). Investment decisions are often made by relying on subjective judgements and beliefs based on managers' private information of which their private information can only be verified with vague and delayed feedback. Consequently, fund managers are particularly susceptible to the self-serving attribution bias. Biased self-attribution can lead fund managers to falsely attribute good investment performance of their investment decisions to their own skill while attributing poor past performance to chance or bad luck, leading to unnecessarily high level of overconfidence.

Overconfidence leads individuals to overestimate their abilities and the precision of their knowledge (Frank, 1935; Fischhoff, Slovic, and Lichtenstein, 1977). In the context of financial markets, overconfident investors tend to overestimate their ability to gather and process information and overestimate the precision of their private information. This can lead investors to engage in excessive trading activity (Odean, 1999). Puetz and Ruenzi (2011) find supportive evidence on increased trading activities by fund managers following good performance. Similarly, overconfident fund managers might overweight their privation information following good performance. As a consequence, they might concentrate their holdings in stocks where they falsely believe that they have informational advantages and, leading to excessive deviation from their benchmark indices. Such portfolio decisions driven by misguided beliefs about one's investment skills and information precision eventually harm portfolio performance over time. Thus, assuming some fund managers are subject to self-attribution bias and overconfidence, we should observe higher deviation from funds' benchmark indices after good past performance and inferior investment performance for portfolios with high Active Share.

Although institutional investors such as mutual funds play an increasingly dominate role in the financial market, there are only few studies that analyses the behaviors of these professional investors who can also be susceptible to behavioral biases and heuristics such as overconfidence. Puetz and Ruenz (2011) investigate overconfidence among equity mutual fund managers by looking at the relationship between past performance and subsequent turnover ratio. Consistent with the prediction from the theoretical studies in the behavioral finance literature, these authors provide strong evidence showing that fund managers tend to engage in excessive trading following good past performance. In particular, they find that subsequent turnover ratios are significantly positively related with past performance for those managers with performance in the top quintile in the previous year. More interestingly, a non-linear relationship between past performance and turnover ratio is observed by these authors: past losers are also more likely to have high subsequent turnover rates. However, Puetz and Puenz (2011) do not examine the potential impact of overconfidence following good past performance on subsequent performance.

Choi and Lou (2010) aim to directly investigate whether mutual fund managers are subject to the self-serving attribution bias by using Active Share as a proxy for confidence. They find a significant positive relationship between the sum of positive past performance and the subsequent Active Share level, suggesting that confirming public signals as reflected on the sum of positive past performance boots managers' overconfidence. These authors also find that this tendency to self-attribute is significantly more pronounced for less experienced managers. Choi and Lou (2010) also try to look at the impact of overconfidence on subsequent performance. They argue that if managers are subject to the self-serving attribution bias and therefore make sub-optimal investment decisions and portfolio allocations, these managers should experience deteriorating future performance. The find evidence to this hypothesis by mainly testing the relationship between the sum of positive past performance on future performance. Their approach, however, might be problematic. The sum of positive past performance can be highly correlated with the overall past performance. One might argue that the observed negative relationship between the sum of positive past performance and subsequent performance could mainly be driven by the fact that superior past performance will eventually revert to mean in the absence of skill.

Eshraghi and Taffler (2014) apply a different approach to examining managerial overconfidence by content analyzing the report managers write to their investors. Using a range of proxies for overconfidence based on content analysis, they are able to show that mutual fund managers who generate superior past performance become overconfident, and that excessive confidence is significantly negatively associated with subsequent performance. More interestingly, they reveal an inverted U relationship between managerial confidence level and subsequent performance. Specifically, managers with normal confidence outperformance their peer mangers who exhibit under- or overconfidence. A trading strategy based on shorting funds managed by abnormal overconfident managers and going long in funds with moderately confident managers yields economically significant positive risk-adjusted returns.

There are several recent studies closely related to the overconfidence of professional investors. Looking at currency markets, O'Connell and Teo (2009) show that institutions tend to increase their risk following gains and these authors argue that such performance-dependent behavior is consistent with overconfidence. Nikolic and Yan (2014) investigate the impact of investor overconfidence on firm value and corporate decisions. These authors show that firms with more overconfident professional investors are relatively overvalued and these firms issue more equity and make more investments.

Overall, behavioral biases and heuristics that are grounded in the cognitive psychology literature have been increasingly applied in financial contexts. In particular, overconfidence is viewed in the behavioral finance literature as one of the most well-documented psychological attributes that can be highly influential in shaping decisions of economic agents. In fact, Plous (1993) suggests that there is no bias is "more prevalent and more potentially catastrophic than overconfidence" in the field of judgement and decision-making. There is an extensive theoretical and empirical literature investigating how overconfidence among corporate managers and retail investors impact corporate decisions and individuals' trading behaviors. However, there is much less, and in general none inconclusive, empirical evidence on the effect of overconfidence among professional investors. Given the increasing importance of professional investors in the financial markets, it is particularly interesting to examine whether professional investors who are usually believed to be rational or at least more rational than individual investors, are also subject to the self-serving attribution bias and overconfidence, and whether and to what extent such biases might impact investment performance.

### 3. Research Questions

There is an extensive literature investigating the performance of professional investors such as mutual fund managers, exploring whether superior performance is associated with certain fund characteristics and attributes, and also testing whether particular investment strategies are able to generate superior performance. These studies usually view fund managers as a class of sophisticated investor who gather and process information efficiently and make rational investment decisions in financial markets but overlook the possibility that these professional investors might also be susceptible to behavioral biases and heuristics such as overconfidence that can be significantly influential in shaping their investment decisions.

Despite the extensive studies looking at overconfidence among corporate managers and retail investors, the behavioral finance literature has not yet provided conclusive evidence on whether mutual fund managers are prone to overconfidence. Motivated by experimental studies in the psychology literature showing that professionals (e.g., mutual fund managers) tend to be more overconfident than laymen (e.g., Griffin and Tversky, 1992; Glaser, Langer and Weber, 2010), this paper aims to remedy the research gap in the literature by examining overconfidence among a large sample of US actively managed equity funds. In particular, this paper explores what the extent that mutual fund managers are subject to the self-attribution bias and prone to overconfidence.

The nature of the asset management industry can expose professional fund managers to the self-serving attribution bias and overconfidence. Fund managers are under intensive and constant competition to outperform peer managers who are equally qualified; they are swamped with incomplete information that is often conflicting and open to competing interpretations; they have to make investment decisions by relying on subjective judgements and beliefs; they have to be exceptional and they have to believe that they are exceptional (Tuckett and Taffler, 2012). In such financial markets where investors can only observe the quality of their private information and the precision of their own beliefs regarding to the underlying value of the assets through delayed and noisy feedbacks, they may overestimate their abilities and increase their confidence level upon observing good performance while they are more likely to attribute failure to external factors and thus lower their confidence levels to a less extent following poor performance. More specifically, fund managers are more likely to revise the precision of their privation information and own beliefs upward too much after good performance while revising precision downwards too little after poor performance. In this scenario, these biased judgmental processes would lead managers to accumulate unnecessary confidence on their abilities over time, eventually resulting into excessive overconfidence. As a consequence, they would be likely to engage in abnormal trading activities. In particular, they overweight the precision of their private information and concentrate their holdings in stocks where they believe that they have information advantages, leading to excessive deviation from their benchmark indices (e.g., high Active Share). Thus, our conjecture is that, if mutual fund managers are subject to the self-attribution bias and overconfidence, we should observe a significantly higher Active Share after good past performance. However, if mutual fund managers are truly skilled and are invulnerable to self-attribution bias and overconfidence, no significant relationship between past performance and subsequent Active Share should be found.

Considering the dominate role of institutional investors in the stock market, it is natural to ask whether potential overconfidence of asset managers might impact their investment performance. This paper seeks to investigate the impact of fund manager confidence on subsequent performance and in particular whether a potential non-linear relationship exists between fund manager confidence and their future performance. The conjecture is that, if fund managers are subject to self-attribution bias and are overconfident, aggressive deviations from benchmark indices (e.g., high Active Share) should be harmful to portfolio performance, because such deviations are more likely to be driven by managers' private information with overestimated precision. On the other hand, moderate portfolio deviations from benchmark indices that might mainly represent managerial skills should generate superior performance.

Consequently, we should observe a significant negative relationship between excessive overconfidence and future performance but a significant positive relationship between normal confidence and subsequent portfolio returns.

There is a large body of literature on the determinants of mutual fund flows. The majority of the studies examine the impact of past performance on fund flows (e.g., Sirri and Tafano, 1998; among others) and show that investors tend to chase past winners but fail to sell past losers to the same extent. Other important determinants of fund flows include fund expense (Barber, Odean, and Zhang, 2005), fund advertising (Jain and Wu, 2000; Gallaher, Kaniel, and Starks, 2015), media coverage (Kaniel, Starks, and Vasudevan, 2007), fund attribute (Bollen, 2007), and fund manager characteristics (e.g., Wermers, 2003; Niessen-Ruenzi and Ruenzi, 2013; Kumar, Niessen-Ruenzi, and Spalt, 2014). However, these is no work up to date relating psychological attributes such as the overconfidence of fund managers to investor flows. This paper therefore is the first attempt of which we are aware to explore the relationship between psychological attributes of fund managers and fund flows, and investigate whether the level of confidence level exhibited by fund managers is associated with subsequent investor flows, and more generally how and why fund investors' response to mutual fund manager overconfidence. The conjecture is that, if investors are aware of the potential consequence of overconfidence and rationally react to managerial overconfidence by withdrawing their assets from overconfident managers, a negative relationship between flows and confidence level should be observed. If they irrational chase funds with overconfident managers who choose excessively high Active Share, a positive relationship should be observed.

To summarize, this paper aims to contribute to the literature on overconfidence among professional investors by looking at a large sample of US actively managed equity funds. In particular, this paper asks whether fund managers are subject to the self-serving bias and overconfidence and investigates the potential impact of managerial overconfidence on their subsequent performance. This paper also seeks to understand how mutual fund investors respond to potential fund manager overconfidence.

## 4. Methodology

### 4.1 Measuring fund manager confidence levels

A key challenge for any study of investor overconfidence is to find a good measure of overconfidence. Researchers have to rely on personal characteristics that are related to overconfidence in the psychology literature such as gender (Prince, 1993; Lundeberg, Fox, and Puncochar, 1994) or the behaviors of overconfident investors that are predicted from theoretical models. For instance, Odean (1998) shows theoretically that overconfidence leads to higher trading activity, larger positions in risky assets, more concentrated portfolios and greater risks. Intuitively, the mechanism is that overconfident investors overestimate the precision of their private information and put too much weight on this information. This eventually leads investors to trade too heavily based on their private information. In the context of professional investors, an alternative proxy for confidence level is the Active Share of Cremers and Petajisto (2009), calculated as the sum of absolute deviations from one's benchmark index. The hypothesis is that, overconfident fund managers overweight stocks in their portfolio for which they have access to private information with overestimated precision and put too little weight on other stocks and eventually deviate too far from their benchmark indices as reflected in a high Active Share level.

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

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

Where $weight_{j,t}^{fund}$ is the weight of stock j in the fund's portfolio at time t, and $weight_{j,t}^{index}$ is the weight of the same stock j 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. To intuitively illustrate Active Share, consider a new mutual fund starts to invest 100% of its cash into the S&P 500 index and eliminates half of the stocks in the index and re-invests the cash generated into the other half of the stocks. This mutual fund then would only have 50% overlap with its benchmark index, thus generating an Active Share of 50%. For a mutual fund with only stock positions and no leverage and short positions, the Active Share of this mutual fund will always lie between 0% and 100%.[2] Furthermore, changes in Active share level are calculated as the difference of Active Share level between two reports of mutual fund holdings, for the purpose of additional tests of managerial overconfidence.

[2] Cremers and Petajisto (2009) and Petajisto (2013) argue that an Active Share larger than 60% can be viewed as active management.

Although mutual funds are required by the SEC to disclose their self-declared benchmark indices in the fund prospectuses after 1998, such data are not available in any existing public database. Determining the benchmark index for a large sample of mutual funds is not an easy task. Petajisto (2013) use few snapshots of the "primary benchmark index" as collected by Morningstar from fund prospectuses. However, this approach may not only suffer from limited data on the benchmark in the fund prospectus but also can potentially lead to biased estimation. Mutual funds can strategically pick the benchmark index that does not realistically reflect the risk exposure of their holdings. Cremers and Petajisto (2009) take a different approach to determine the benchmark index for each fund by looking at calculated Active Share levels against all available benchmark index and picking the benchmark indices with the lowest Active Share as that fund's benchmark. Following Cremers and Petajisto (2009) this paper uses the smallest Active Share (activeshare_min) as the measure of active management and assigns the corresponding best-fit benchmark index (index_min) to each fund.

### 4.2 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. This paper estimates the following regression:

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

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 given by 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 returns 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 in this paper, we run the regression for each fund *i* and each year and collects the time series of the estimated intercept for each fund *i* as the risk-adjusted performance over time. This paper also estimates the one-factor CAPM alpha and the Fama - 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.

Additionally, this paper looks at the realization of extreme (good or bad) performance outcome by estimating the performance extremity measure that is based on Bär, Kempf and Ruenzi (2011) who examine the effects of the management structure of mutual funds on subsequent risk taking behaviors and performance extremity. For each fund *i* in each time period *t*, the 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 at the same time period. These numbers are then normalized by dividing them by the average absolute difference of all *n* funds in the corresponding market segment and respective time period:

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

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*. A higher level of performance extremity measure indicates a more extreme performance outcome, either good or bad. After normalizing the performance extremity measure, a fund with exact average performance within its market segment by construction has a performance extremity of 1 while a fund with extreme performance relative to all funds in its market segment would demonstrate a performance extremity that is above 1.

### 4.3 Measuring fund flows

Following prior literature (e.g., Chevalier and Ellison 1997; Sirri and Tufano 1998), net investor flow of individual fund share class i at time t is estimated as:

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

Where $TNA_{i,t}$ is the total net asset 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; $MGN_{i,t}$ is the increase in total net asset for individual fund share class i at time t due to fund mergers. Since the CRSP Mutual Fund Database does not provides the exact data on which the merger occurs, this paper follows Lou (2012) using the last net asset value (NAV) report date as the initial estimate of the merger date and, in order to avoid the obvious mismatches generated by this initial estimate, this paper matches a target individual share class to its acquirer from one month before its last NAV report date to five months later, a total of 7 months matching period. Then the month in which the acquirer has the smallest absolute percentage flow, after subtracting the merger, is assigned as the merge event month. 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 flow. Monthly fund flows during the corresponding quarter are then aggregated into the quarter flow. This paper assumes that investor inflow and outflow take place at the end of each quarter and investors reinvest their dividends and capital appreciation distributions in the same fund.

## 5. Data and Sample

### 5.1 Data on mutual fund holdings and returns

Mutual fund holdings data are obtained from Thomson Reuters Mutual Fund Holdings database (formerly known as CDA/Spectrum Database), which is based on mandatory quarterly reports filed with the SEC and from voluntary reports generated by the mutual funds themselves. Thomson Reuters Mutual Fund Holdings database provides information including fund identification (fundno), report date (rdate), file date (fdate), stock identification (cusip), and number of shares held (shares).

The CRSP Mutual Fund Database provides information on monthly fund net returns (ret), monthly total net assets (tna), monthly net assets value (nav) different types of fees including annual expense ratio (exp_ratio) and management fee (mgmt._fee), turnover ratio (turn_ratio), investment objectives, first offer date (first_offer_dt) and other fund characteristics for each share class of every US open-end mutual fund. Following the standard procedure in the literature, for funds with multiple share classes with the same back-up portfolio, this paper computes the sum of total net assets under management (tna) in the each share class to arrive at the total net assets of the fund. For monthly net returns, expense ratio and turnover ratio at fund level, this paper estimates the value-weighted average across share classes based on the total net assets of each share class. For all other fund variables such as fund name (fund_name), first offer date (first_offer_dt), management company name (mgmt._name), portfolio manager name (mgr_name), this paper selects the variables from the share class with highest total net assets and longest history.

This paper maps the Thomson Reuters Mutual Fund Holdings Database with the CRSP Mutual Fund Database by using the MFLINKS Database. This database provides the key identification Wharton Financial Institution Center Number (wficn) for portflios that can reliably link fund identification in CRSP Mutual Fund Database (crsp_fundno) and portfolio identification in the Thomson Reuters Mutual Fund Holdings Database (fundno). This paper also tries to correct any matching errors after this standard data merging procedure by looking at fund names in both databases manually.

**5.2 Active Share and stock price data**

Active Share data are obtained from Petajisto Website,[3] which is the updated main data set from Petajisto (2013). To calculated active share, one needs data on portfolio holdings of mutual funds as well as the composition of their benchmark indices. Petajisto (2013) includes a total of 19 indices used by mutual funds in the sample where the index holdings data are obtained from the index providers. The indices are Standard & Poor's (S&P), Russell Investment, and Dow Jones/Wilshire Associates, including their common large-cap, mid-cap, and small-cap indices as well as growth and value indices. The detailed description to construct active share dataset can be found in Petajisto (2013).

Data on stock identification, stock return, delisting return, share price, trading volume, cumulative price adjustment factors, cumulative shares adjustment factors, and total outstanding shares as well as other stock characteristics are obtained from the CRSP stock price database. This CRSP price dataset[4] is then merged with the Thomson Reuters Mutual Fund Holdings database by matching stock identification (cusip) and holding report date (rdate) and file date (fdate). The number of shares held (shares) in the portfolios 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. Data used to estimate book value of equity for stocks as in Daniel and Titman (1997) are retrieved from Compustat, including shareholders' equity (SEQ), deferred taxes (TXDB), investment tax credit (ITCB), and preferred stock (PREF). Industry classifications (SIC) are obtained from the CRSP stock file and Compustat whenever available.

3 http://www.petajisto.net/data
4 Stock return is adjusted for delist events, share price is adjusted by cumulative price adjustment factors, and share outstanding is adjusted by cumulative shares adjustment factors.

### 5.3 Sample selection

The focus of the analysis is on actively managed US domestic equity mutual funds for which the holdings data are most complete and reliable. This paper follows and modifies the procedure of Kacperczyk *et al* (2008) to select US domestic equity mutual funds. This paper starts with all mutual fund samples in the CRSP Mutual Fund Database and the Thomson Reuters Mutual Fund Holdings database universe and then looks at various investment objective codes including Investment Objective codes (IOC) from the Thomson Reuters Mutual Fund Holdings database, Strategic Insight objective codes (si_obj_cd), Weisenberger classes codes (wbrger_obj_cd), Lipper classification codes (lipper_class) and CRSP policy codes (policy) taken from the CRSP Mutual Fund Database. This paper requires average equity holdings (avrcs) to be at least 70% and the percentage of matched US stock holdings to be at least 60%. This paper also excludes sector funds and funds with total net assets under management below $10 million. These selection criteria effectively exclude balanced, bond, money market, international, sector funds as well as those funds not invested primarily in equity securities. Additionally, this paper eliminate index, ETF, exchange target, and target date funds by looking at the name of funds. This screening procedure generates a final sample of 80651 fund-quarter observations with a total of 2740 unique US domestic equity mutual fund samples in the period 1980 to 2009. Appendix A provides further details on the sample selection.

### 5.4 Summary Statistics

Table 1 presents the descriptive statistics for the equity funds included in our sample. Panel A reports the total number of domestic equity mutual funds in each 5-year period along with the fund characteristics. Consistent with the literature, the past three decades witnesses a tremendous growth in the size of mutual fund industry in terms of number of funds and the average total net assets under management. Despite the increasingly important role of mutual funds in financial market, it is interesting to see that there is a significant decreasing trend of active management in the industry over the sample period. Equity funds average Active Share dropped from 90.5% in 1980 to 81.7% in 1990, and to 74.0% in 2009, the end of our sample period. Panel B shows the time series summary statistics of sample funds categorised by investment objectives. Relative to other funds, micro-cap funds exhibit the highest Active Share and they have the highest expense ratios, perhaps reflecting the cost of their active management style. On the other hand, growth & income funds and income funds were much less active in terms of in portfolio stock allocations and they also tend to trade much less than funds in other investment objective groups.

Table 2 reports the detailed summary statistics of Active Share, our main proxy for overconfidence, across market segments. It highlights the structural differences in Active Share among investment objective categories. In particular, both micro-cap and small-cap funds exhibit significantly higher levels of Active Share in terms of mean and median value relative to other investment categories. While similar maximum values of Active Share across segments are observed, micro-cap and small-cap funds exhibit considerably higher level of Active Share for the upper quartile, median and lower quartile levels.

To demonstrate the structural difference of Active Share according to investment objective, we also show the distribution of Active Share levels in Figure 1. As we can see, on average micro-cap and small-cap mutual funds (or aggressive growth-oriented funds) disproportionately have very high Active Share level in the range of 90% to 100%. Almost half of sample funds in this range are from micro-cap and small-cap funds. There is also a significant skewness to high Active Share for mid-cap funds. In contrast, growth funds and growth & income funds show a more normal distribution with mean in the range of 75-80% and 70-75%, respectively. Such significant structural variation can potentially lead to false implications about the relationship between Active Share and subsequent performance as portfolios of funds with high Active Share merely reflect the exposure to micro-cap and small-cap funds.

## 6. Empirical Results

### 6.1 Overconfidence and Past Fund Performance

This paper examines whether fund managers become overconfident after good past performance by using the sum of absolute deviation from the fund's benchmark index (i.e., Active Share) to proxy for fund manager confidence level and relating this to the fund's past performance. The conjecture is that outstanding past performance might make fund managers who are subject to self-attribution bias believe that they are better skilled at picking stocks than they actually are, which eventually leads to an unnecessarily high level of Active Share. Following Cremers and Petajisto (2009), this paper tests for a linear relationship between past performance and Active Share level by running a pooled panel regression of Active Share on fund's past performance and other fund characteristics as following:

$$Activeshare_{i,t} = \alpha + \beta_1 Perf_{i,t-1} + Controls + \epsilon_{i,t} \quad (1)$$

where $Activeshare_{i,t}$ denotes the active share level for fund *i* at quarter *t*, $Perf_{i,t-1}$ is the past performance of mutual fund $i$, one year prior to the current quarter $t$, $Controls$ is a vector of control variables relating to fund characteristics in the literature. In order to mitigate the potential endogeneity problem, this paper lags all control variables by one quarter, except the expenses and turnover ratio which are lagged 1 year due to lack of quarterly data availability. Specifically, this paper includes fund age (natural logarithm of age in years since first offer date), fund size (natural logarithm of total net assets under management in millions of dollars), expense ratio (in percentage per year), turnover rate (in percentage per year), manager tenure (natural logarithm of tenure in years current manager takes over the place) and the percentage flow (the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$). To mitigate the impact of outliers on the estimates, we follow the standard procedure in the literature and winsorises Flow and Turnover at the 1% level. [5] We also include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effects.

Table 3 reports the results of regressions of Active Share level to past performance and a variety of fund characteristics from Model (1). Column (1) shows that past performance measured as the Carhart (1997) four-factor alpha is positively related to current Active Share level. The estimated coefficient on past performance is 0.57 and statistically significant at the 1% level. To rule out the possibility that such positive performance-Active Share relationship is driven by other fund characteristics related with Active Share, Column (3) introduces a variety of control variables of fund characteristics that commonly used in the literature. Surprisingly, the magnitude of the estimated coefficient on past performance increases to 1.10, statistically significant at the 1% level, after controlling for other fund characteristics. These results indicate that fund managers tend to have a higher level of Active Share following good performance. The sign and magnitude of the coefficients of control variables for Model (1) are broadly in line with Cremers and Petajisto (2009) and Petajisto (2013).

In practice, mutual fund managers are more likely to be evaluated based on their relative performance compared to the other equity fund managers within the same market segment. There are a body of studies in the literature that use an ordinal performance measure (performance ranks) to explain investor flows. Their findings in general show that good past

[5] e.g., Kacperczyk, Nieuwerburgh and Veldkamp (2014)

performance attracts investor flows and more importantly ordinal performance measures explain inflows better than cardinal performance measures do. Since mutual fund managers are mainly compensated by the amount of total assets under management which is primarily driven by how much flows they can attract from the market, they are motivated to compete with their peer managers for inflows, and therefore managers are mainly concerned about their relative positions. Puetz and Ruenzi (2011) relate turnover ratio to relative performance positions and provide evidence that good past performance relative to other peer managers leads to a higher turnover ratio. This paper follows this approach to capture the impact of past performance on the confidence level of mutual fund managers reflecting by the deviation from their benchmark indices. Specifically, this paper constructs the performance rank of a fund by ordering all funds belonging to a specific market segment in each quarter end based on past performance and then assigns a rank number to each fund for each quarter. This rank number is normalized to be equally distributed between 0 and 1. For each quarter, the fund with best past performance by construction has the normalized performance rank of 1 and the fund with the worse past performance has the normalized performance rank of 0. Using this performance rank, this paper runs the following regression:

$$Activeshare_{i,t} = \alpha + \beta_1 PerfRank_{i,t-1} + Controls + \epsilon_{i,t} \quad (2)$$

where $Activeshare_{i,t}$ denotes the active share level for fund *i* at quarter *t*, $PerfRank_{i,t-1}$ is the normalised rank of fund past performance, measured over one year period prior to current quarter $t$¸ $Controls$ is the vector of control variables relating to fund characteristics.

Table 4 summarises the results of the regressions of Active Share on past performance rank. Consistent with what we observe in Table 3, a higher past performance rank relative to all other funds in the same market segment is associated with a higher level of Active Share. The estimated coefficients of past performance rank are both statistically significantly positive at the 1% significance level, before and after controlling for fund characteristics. The coefficient on past performance in Column (3) suggests that an increase of past performance rank by 0.2 is associated with an increase of Active Share level by about 0.72%, holding all other things constant. Overall, consistent with Cremers and Petajisto (2009), there is a general positive relationship between past performance and current Active Share level and this relationship is statistically significant at the 1% significance level after controlling for other fund characteristics, which indicates that fund managers with good past performance tend to have higher level of Active Share. However, the relationships found in both Model (1) and Model

(2) are not economically significant, suggesting a potential non-linear relationship between past performance and fund manager confidence level.

The potential non-linear relationship between past performance and Active Share level might arise for following reasons: first, it is not surprising to see that only fund managers with outstanding past performance are more prone to self-attribution bias and believe that they are better than average. Consequently, these overconfident fund managers are more likely to allocate their portfolios' assets in an aggressive way that they might deviate far more from their benchmark indices than others. Neither poor performing fund managers nor those with average past performance would be likely to become overconfident. Therefore this paper expects a positive relationship between past performance and Active Share level among very successful fund managers with superior past performance. Second, in attempts to increase the chance to catch up their positions, fund managers with poor past performance might be motivated to gamble otherwise they might face career risk. Such career incentive might lead these poorly performing managers to engage in aggressively deviating from their target benchmark indices and therefore a negative relationship between past performance and the Active Share level for fund managers with poor past performance. Third, this paper expect to find no strong or weaker relationship between past performance and the Active Share level for fund managers with average performance. Overall, a U-shape relationship between past performance and the Active Share level is expected.

Following Puetz and Ruenzi (2011) who find strong evidence of a non-linear relationship between past performance and turnover ratio, this paper uses two alternative modelling approaches to capture the potential U-shape relationship.

First, this paper applies 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 quintile and the top past performance quintile by running the following regression:

$$Activeshare_{i,t} = \alpha + \beta_1^L LOW_{i,t-1} + \beta_1^M MID_{i,t-1} + \beta_1^T TOP_{i,t-1} + Controls + \epsilon_{i,t} \qquad (3)$$

where:

$LOW_{i,t-1} = \min\,(PerfRank_{i,t-1}, 0.2)$

$MID_{i,t-1} = \min\,(PerfRank_{i,t-1} - LOW_{i,t-1}, 0.6)$

$TOP_{i,t-1} = PerfRank_{i,t-1} - (LOW_{i,t-1} + MID_{i,t-1})$

and $Activeshare_{i,t}$ denotes the active share level for fund *i* at the quarter *t*, $Controls$ is the vector of control variables relating to fund characteristics. A negative (positive) coefficient for the bottom (top) performance quintile is expected while there is no directional expectation for the three middle quintiles of past performance. But, we should expect a weaker impact of past performance on manager's confidence level reflecting in the Active Share level in terms of absolute value than the other two quintile groups.

Second, this paper estimates a quadratic relationship between past performance and Active Share by modelling past performance in linear and quadratic terms:

$$Activeshare_{i,t} = \alpha + \beta_1 PerfRank_{i,t-1} + \beta_2 \left(PerfRank_{i,t-1}\right)^2 + Control + \epsilon_{i,t} \qquad (4)$$

Where $Activeshare_{i,t}$ denotes the active share level for fund *i* at the quarter *t*, $PerfRank_{i,t-1}$ is the normalised rank of fund past performance, measured over one year prior to the current quarter $t$, $\left(PerfRank_{i,t-1}\right)^2$ is the squared normalized rank of fund past performance, $Controls$ is the vector of control variables relating to fund characteristics. For this quadratic regression, this paper expects a negative coefficient for the linear term and a positive coefficient for the quadratic term so that the shape of the non-linear relationship between past performance and Active Share is confirmed to be U-shape.

Estimation results for Model (3) are presented in Table 5. Our main focus is on the coefficient for the impact of past performance on subsequent Active Share level in the top performance quintile. The estimated coefficient on $TOP_{i,t-1}$ is positive and it is statistically significant at the 1% level at all model specifications. In unreported analysis, this significant positive relationship between a fund's past performance and its subsequent Active Share level 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 $TOP_{i,t-1}$ are typically significant at the 1% level. The reported impact of past performance on Active Share is also economically significant. Assuming all other effects constant, there is a considerable difference in Active Share level between the very best performing fund (rank 1) and a fund at the bottom of the top performance quintile (rank 0.8) of about 12% ($0.60\times0.2 = 0.12$).

In contrast, the coefficient on $LOW_{i,t-1}$ suggests that there is an economically and statistically significant negative relationship between past performance and subsequent performance for the bottom performance quintile. By holding all other variables constant, we find a considerable difference in Active Share level between a fund at the top of the bottom performance quintile (rank 0.2) and the worst performing fund (rank 0) of about -8.6% ($-0.43\times0.2 = -0.086$), meaning that funds that experience poor past performance tend to engage in gambling by choosing higher Active Share level, perhaps in an attempt to increase the chance to catch up their positions in the future. Furthermore, estimated coefficient for the three middle performance quintiles is positive and statistically significant at the 1% level in the model specification with controls for other fund characteristics. But the magnitude of the effect is dramatically smaller comparing to the top and bottom performance quintiles. We only observe a 1.2% increase of Active Share level from the funds at the bottom of the middle quintiles to the funds at the top of the middle performance quintiles. Table 6 reports the results for the quadratic specification of Model (4). As expected, we find significant negative coefficients for the linear impact of past performance and significant positive coefficients for the quadratic term, which therefore confirms the U-shaped relationship between past performance and Active Share reported in Table 5.

To investigate whether good past performance is associated with an increase of Active Share, we run regressions of changes in Active Share on past performance, using piecewise regression approaches. Results from piecewise regressions are presented in Table 7. A positive and significantly positive relationship between past performance and changes in Active Share level is found for fund managers who are in the top quintile of past performance while no significant relationship for other lower quintiles of past performance, after controlling for fund characteristics. Estimated coefficient on $TOP_{i,t-1}$ is positive and it is statistically significant at 1% level regardless of model specifications. The effect of past performance on changes in Active Share is also economically significant. Holding all other effects constant, there is a considerable difference in changes in Active Share level between the very best performing fund (rank 1) and a fund at the bottom of the top performance quintile (rank 0.8) of about 1% ($0.049 \times 0.2 = 0.0098$), suggesting that fund managers tend to increase their Active Share levels following outstanding performance.

Team managed mutual funds are increasingly popular in the industry in recent years (Bär, Kempf and Ruenzi, 2011). A natural question is to look at how the investment decisions made by teams differ from those of individuals. The literature provides two competing hypotheses on the impact of management structure. The group shift hypothesis (Moscovici and Zavalloni, 1969; Hogg, Turner and Davidson, 1990; Kerr, 1992) suggests that individuals make less extreme decisions than teams do because the opinions of team members are likely to shift towards the opinion of the dominant person, which eventually leading to aggressive decisions. Solo managed funds are less likely to be at risk of becoming overconfident after good past performance than team managed funds who are prone to group think bias. Additionally, group think would also lead to more aggressive bets after poor past performance. On the other hand, the diversification of opinions hypothesis suggests that individuals who are more prone to self-attribution bias might act more irrationally and therefore more likely to be at risk of being overconfident after good past performance and of gambling after poor past performance while teams are more rational than individuals (Cooper and Kagel, 2005; Kocher and Sutter, 2005) and they make less extreme decisions (Sah and Stigllitz, 1986 and 1988). Recent work by Bär, Kempf and Ruenzi (2011) provides supporting evidence for the diversification of opinions hypothesis. They show that team managed mutual funds make less aggressive style bets, their portfolios are less industry concentrated and they achieve less extreme subsequent performance.

Motivated by Bär, Kempf and Ruenzi (2011), this papers investigates the potential difference in responses to past performance between solo managed and team managed mutual funds by interacting the performance quintiles with a solo management dummy and adding additional solo management dummies without interaction to capture the constant effect between solo and team managed funds. The regression model is:

$$\begin{aligned} &Activeshare_{i,t} \\ &= \alpha + \beta_1 Solo_{i,t-1} + \beta_2^L Solo_{i,t-1} LOW_{i,t-1} + \beta_2^M Solo_{i,t-1} MID_{i,t-1} + \beta_2^T Solo_{i,t-1} TOP_{i,t-1} \\ &+ \beta_3^L LOW_{i,t-1} + \beta_3^M MID_{i,t-1} + \beta_3^T TOP_{i,t-1} + Controls \\ &+ \epsilon_{i,t} \qquad (5) \end{aligned}$$

Where $Solo_{i,t-1}$ denotes a dummy variable equal to 1 if mutual fund $i$ is single-managed during the period $t$-$1$ to $t$, and zero otherwise. All other explanatory variables and control variables are defined before. Under the group shift hypothesis, we should observe that solo managed funds act more rationally and therefore less likely to becoming overconfident after good past performance and to gamble after poor past performance. Thus, a positive (negative) coefficient is expected for the interaction term of bottom (top) performance quintile. Under diversification opinion hypothesis, we should observe that solo managed funds act more irrationally therefore a negative (positive) coefficient is expected for the interaction term of bottom (top) performance quintile. Model (5) results are presented in Table 8.

The estimated coefficient of the single-managed fund dummy variable $Solo_{i,t-1}$ is positive and statistically significant at the 10% level, meaning that solo managed mutual funds on average have a marginal higher Active Share of 1.18% than funds managed by a team. More interestingly, the effect of past performance on Active Share level interacted with the solo dummy for the top performance quintile is positive and statistically significant at the 5% level, suggesting that solo-managed funds are more prone to self-attribution bias and are more likely to be as risk of becoming overconfident than team-managed peer funds following outstanding performance, as reflected by about 1.93% (($0.0965 \times 0.2 = 0.0193$) higher Active Share of solo-managed funds than their team-managed counterparties. For the bottom performance quintile, the effect of past performance on Active Share level interacted with the solo dummy is negative and statistically significant at the 1% level. This is consistent with the view that solo-managed funds are more likely to increase Active Share level after bad performance. Overall, these results of significant difference in Active Share between solo- and team-managed funds directly support the diversification opinion hypothesis which predicts that solo-managed funds are more irrational than team-managed funds and are more easily subject to behavioral bias.

For robustness check purposes, we use a fund's relative position of Active Share level to other funds in the same market segment (Active Share rank) as an alternative proxy for fund manager confidence level and re-run all the regressions of Active Share rank or changes in Active Share rank on past performance using standard linear approach, and piecewise and quadratic non-linear approaches. We find consistent results showing that fund managers who experience outstanding performance are more likely to choose a significantly higher level of Active Share relative to other funds in the same market segment and they are more likely to increase their

Active Share rank. Furthermore, we test our hypothesis by using the Fama - Macbeth (1973) regression method. This approach 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. In unreported tables, results are all robust with regard to the Fama and Macbeth (1973) regression method at similar significant levels. Therefore, our findings provide strong evidence showing that mutual fund managers are prone to overconfidence following their past successes and such tendency appears to be stronger among solo-managed funds.

To summarize, there is a clear U-shaped non-linear relationship between past performance of mutual funds and their subsequent Active Share level. In particular, fund managers tend to choose a higher Active Share level, and these fund managers are also more likely to increase Active Share following their past successes. Such bias is more pronounced among solo-managed mutual funds. These findings are consistent with our conjecture that fund managers become overconfident after good past performance.

### 6.2 Overconfidence and Subsequent Fund Performance

Consistent with the prediction from overconfidence models in the literature, our results thus far have shown that outstanding past performance of mutual funds leads to excessive overconfidence, as reflected in their significantly higher level of Active Share and higher tendency to increase Active Share. Drawing on the behavioral finance literature, we would expect such sub-optimal investment decisions and excessive trading activities caused by overconfidence will eventually lead to deteriorating future performance. Thus, our conjecture is that, if mutual fund managers are overconfident and are subject to self-attribution bias following their past successes, they might believe that they possess better than average skills. Over time, these managers could potentially over-estimate the precision of their private information and therefore engage in excessive trading activities based on these over-estimated information. If this is true, we should observe that extremely high levels of Active Share will be associated with diminished subsequent performance.

However, a high level of Active Share might not necessarily be an indicator of overconfidence. It is also possible that the observed higher levels of Active Share after good past performance reflect optimal portfolio allocation and rational investment decisions. After updating the precision of managers' private information and their true skills, it is a rational response for truly skilled managers to put larger weights on their private information, leading to a greater deviation from their benchmark indices. Such deviation by rational managers should then on average result in better portfolio allocation to good stocks and eventually lead to better subsequent performance. Under this hypothesis, we should observe high levels of Active Share being associated with superior subsequent performance.

Indeed, Cremers and Petajisto (2009) and Petajisto (2013) provide evidence consistent with high Active Share predicting superior subsequent performance. Since the publication of Cremers and Petajisto (2009), there is an ongoing debate on Active Share in the investment community. On one hand, some investment houses support Active Share and voluntarily disclose the Active Share level of their portfolios under management to the public and their investors while others view Active Share as a flawed metric. On the other hand, investors seem to increasingly view Active Share as a convenient and flawless indicator of managerial skills to generate future performance. The main contribution of Cremers and Petajisto (2009) and Petajisto (2013) are to provide a powerful and intuitive tool to assess active management by distinguishing active portfolios from passive portfolios and to thereby justify management fee charged to fund investors.

However, the documented predictive power of Active Share might be over-estimated. Cremers and Petajisto (2009) and Petajisto (2013) sort and categorize mutual funds into groups based on their level of Active Share and look at the subsequent performance of those Active Share groups of mutual funds. Such approach without taking into account of the characteristics of funds and their corresponding market segments can lead to biased implications. In particular, the distribution of Active Share levels are implicitly correlated with the investment objectives of the respective portfolio. By segmenting mutual funds based on their investment objectives, this paper shows that Active Share levels vary structurally across funds' investment objective categories. In particular, on average micro-Cap and small-Cap mutual funds (or aggressive growth-oriented funds) disproportionately have very high Active Share levels. It is possible that the documented positive relationship between high Active Share and superior subsequent performance is primarily attributed to the exposure of these aggressive growth-oriented funds. Similarly, a recent report by Fidelity Investment (2014) shows the disproportionate numbers of small-Cap funds with very high Active Share level comparing to large-Cap funds. A small-cap fund with an average Active Share of 80% can be categorized as low Active Share compared to other funds in the same market segment while a growth & income fund with an average Active Share of 80% can be viewed to have high Active Share among its peer funds.

To overcome this structural difference in Active Share level across different investment objective categories, this paper uses a modified approach to assess active management by ranking funds within their corresponding market segment based on Active Share level. Specifically, for each quarter, this paper constructs 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 assigned a rank number and this rank number then is normalized so that ranks are evenly distributed between 0 and 1. The fund with highest Active Share level within its market segment gets assigned the rank 1 while the fund with lowest Active Share level within its market segment has the rank 0. This normalized rank number tells us the relative fund position along the active management spectrum compared to all other funds in the same market segment, and it also allows us to directly compare funds across different market segments.

Although Cremers and Petajisto (2009) apply multivariate regression analysis on the linear relationship between Active Share and excess performance controlling for fund characteristics, it is possible that they overlook any potential non-linear relationship. A potential non-linear relationship between Active Share and subsequent performance may arise for following reasons. First, as we have shown before, fund managers with good past performance tend to have significantly higher Active Share and this tendency is significantly more pronounced among the very best performing managers. Our conjecture is that, if these fund managers are overconfident and are subject to self-attribution bias, excess trading and extremely high Active Share levels are more likely to be motivated by managers' private information which might actually be much less precise than they think. This would lead to sub-optimal portfolio allocation and eventually diminishing performance. If this is the case, we should observe a negative relationship between Active Share and subsequent performance among funds in the top quintile of Active Share. Second, moderate Active Share levels might better reflect managers' normal levels of confidence and more rational investment decisions. Fund managers with normal confidence assess and update their private information in a more rational way. Consequently, it is rational for them to put larger weights on their private information and smaller weights on other stocks from their benchmark indices. In this scenario, these well motivated trading activities should lead to the realization of profitable opportunities and better portfolio allocation, which eventually generates better performance. If this is true, we should observe a strong positive relationship between Active Share and subsequent performance for the four Active Share quintile groups below the top quintile. Thus, overall we expect an inverted U-shaped non-linear relationship between Active Share and subsequent performance that can be masked as the documented positive linear relationship in the literature.

To capture the potential relationship between Active Share and subsequent performance, this paper uses three alternative modeling approaches: (1) we apply a piecewise linear regression approach; (2) we replace the piecewise linear approach by dummies indicating in which decile of Active Share funds the respective fund lies; (3) we estimate a quadratic relationship between Active Share and subsequent performance by modelling Active Share as linear term and as quadratic terms.

Applying a piecewise linear regression approach allows us to estimate slope coefficients for the impact of Active Share on subsequent performance for different quintiles of Active Share separately. Slope coefficients are estimated for the bottom quintile, the three middle quintiles, and the top quintile of segment ranks of Active Share:

$$Perf_{i,t} = \alpha + \beta_1^L LOW_{i,t-1} + \beta_1^M MID_{i,t-1} + \beta_1^T TOP_{i,t-1} + Controls + \epsilon_{i,t} \quad (6)$$

where:

$LOW_{i,t-1} = \min\,(ActiveShareRank_{i,t-1}, 0.2)$

$MID_{i,t-1} = \min\,(ActiveShareRank_{i,t-1} - LOW_{i,t-1}, 0.6)$

$TOP_{i,t-1} = ActiveShareRank_{i,t-1} - (LOW_{i,t-1} + MID_{i,t-1})$

and $ActiveShareRank_{i,t-1}$ denotes the normalized segment rank of Active share for fund *i* during the period of time *t-1* and *t*, and $Controls$ is the vector of control variables relating to fund characteristics. Under the overconfidence hypothesis, we expect positive slope coefficients for the bottom quintile and the three middle quintile of Active Share and a negative slope coefficient for the top quintile of Active Share.

Instead of assuming constant factor loadings across time, this paper builds on the literature by using past data to estimate the Carhart (1997) four-factor model and determine the abnormal performance during the subsequent period.[6] Specifically, for each fund each month, we use 12 months of past monthly fund returns to estimate the coefficients of the Carhart (1997) four-factor models and subtract the expected return from the realized return to determine the abnormal return of a fund. We then calculate quarterly abnormal performance for each fund-quarter observation. This approach takes into account possible time variations in the factor loadings of individual funds and avoids sample selection bias that might arise when excluding young funds without a long return history. Following Cremers and Petajisto (2009), we run pooled panel regressions of fund abnormal performance on all the explanatory variables. In order to mitigate the potential endogeneity problem, we lag all control variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Specifically, as before, we include fund age, fund size, expense ratio, turnover rate, manager tenure and prior percentage flow and prior performance. To mitigate the impact of outliers on our estimates, we winsorise 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 model specifications.

Estimation results for the Model (6) relating to the piecewise linear regression of the abnormal performance based on the Carhart (1997) four-factor model on the bottom quintile, the three middle quintiles and the top quintile of Active Share rank are presented in Table 9. First, the impact of Active Share on subsequent performance is positive for the bottom quintile of Active Share but the effect turns out to be statistically insignificant when including full set of control variables. Second, the slope coefficients for the three middle quintiles of Active Share are all positive and statistically significant at least at the 1% level with the full set of control variables, indicating that there is an economically 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) of 18.75 basis points per quarter ($= 0.003124 \times 0.6 = 0.001875$) or 0.75% on an annual basis, holding other effects constant. Strikingly and perhaps more interestingly, the impact of Active Share on subsequent performance turns to be statistically negative for the top quintile of Active Share. The effect is economically significant: on average funds with the highest segment rank of Active Share

[6] Kacperczyk, Sialm and Zheng (2005) apply a similar approach to look at the relationship between industry concentration of mutual funds and their subsequent abnormal performance.

(Rank 1.0) underperform funds at the bottom of the top quintile of Active Share (Rank 0.8) by about 27.58 basis points per quarter ($= -0.01379 \times 0.2 = -0.002758$) or 1.09% per year. Thus, these results from piecewise linear regressions suggests a clear inverted U-shaped relationship between Active Share and subsequent performance. This is consistent with our conjecture that normal confidence levels of fund managers as reflected in moderate levels of Active Share are associated with better subsequent performance while excessive overconfidence as reflected in extreme high Active Share is significantly associated with diminished future investment returns.

To explore further the relationship of being among the most active funds within the market segment to subsequent performance, this paper applies an alternative approach by replacing the piecewise linear approach by dummies indicating in which decile of Active Share funds:

$$Perf_{i,t} = \alpha + \sum_{n=2}^{10} \beta_n \cdot Dummy_n(ActiveShareRank)_{i,t-1} + Controls + \epsilon_{i,t} \qquad (7)$$

where the expression $Dummy_n(ActiveShareRank)_{i,t-1}$ indicates whether the fund *i* belongs to the segment rank decile *n* according to its Active Share level during time period *t-1* to *t*. For example, $Dummy_{10}(ActiveShareRank)_{i,t-1}$ equals to 1, if the fund belongs to the top decile within its market segment, i.e. if its segment rank of Active Share is between 0.9 and 1.0, and zero otherwise. The lowest decile of Active Share rank is the base decile representing mere index "huggers" and therefore is not included in the regression in order to prevent the independent variables to be linear dependent. $Dummy_n(ActiveShareRank)_{i,t-1}$ gives us the excess subsequent performance of a fund within Active Share decile *n* compared to being the lowest decile within the same market segment.

Table 10 summarizes the results of running the Model (7) on relating to the impact of belonging to a specific Active Share decile within the respective market segment. There is a general increasing trend in the magnitude of the coefficients on Active Share decile dummy variables from $Dummy_2(ActiveShareRank)_{i,t-1}$ up to $Dummy_7(ActiveShareRank)_{i,t-1}$. Estimated coefficients are all positive but only $Dummy_6(ActiveShareRank)_{i,t-1}$ and $Dummy_7(ActiveShareRank)_{i,t-1}$ are statistically significant at the 1% level. The effect of having normal level of confidence, as reflected by moderate Active Share levels, is economically meaningful. In particular, holding other effects constant, the normally confident funds that belongs to the Active Share decile between Rank 0.6 to Rank 0.7 outperform the funds within the lowest decile of Active Share by 28.18 basis points per quarter, or 1.13% on an annual basis. Perhaps more importantly, we observe a decreasing trend of the magnitude of the effect of Active Share to subsequent performance. Of particular interest, the coefficient of the $10^{th}$ decile representing the funds with the highest Active Share within their segment is statistically and economically insignificant, meaning that on average overconfident mutual fund managers are not able to significantly outperform their peer managers who are at the lowest rank of Active Share. Overall, the results of these dummy variables of Active Share demonstrate a similar inverted U-shaped relationship between Active Share and subsequent performance as found in the piecewise linear regression: normal confidence generates excess returns in the future but excessive overconfidence of fund managers hurts portfolio performance.

This paper also applies the quadratic specification as an additional test to confirm the non-linear relationship between Active Share rank and subsequent performance:

$$Perf_{i,t} = \alpha + \beta_1 ActiveShareRank_{i,t-1} + \beta_2 \left(ActiveShareRank_{i,t-1}\right)^2 + Control + \epsilon_{i,t} \qquad (8)$$

where $ActiveShareRank_{i,t-1}$ denotes the normalized segment rank of Active share for fund *i* during the period of time *t-1* and *t*, and $Controls$ is the vector of control variables relating to fund characteristics. Under the overconfidence hypothesis, we expect a positive coefficient on the linear term and a negative estimate on the quadratic term.

Table 11 reports the results for the quadratic specification of Model (8). We find positive coefficients for the linear impact of Active Share on the subsequent performance and negative coefficients for the impact of squared Active Share. Both coefficients are statistically significant. Again, the relationship between confidence level of mutual fund managers and their subsequent performance exhibits a clear inverted U-shape that is similar to what we find before.

To further investigate the impact of overconfidence on subsequent performance, we include the changes in Active Share rank in the piecewise regression in model (6) with Active Share rank and other fund characteristics as control variables. Estimated coefficients on changes in Active Share rank are reported in Table 12. Our results reveal a negative relationship between changes in Active Share rank and subsequent performance: increase of Active Share rank is associated with deteriorated subsequent risk-adjusted abnormal performance. The coefficients on changes in Active Share rank are negative and statistically significant at the 5% significant level in all model specifications. The effect is economically meaningful: on average, a 10% increase of Active Share rank on average leads to a decrease of subsequent performance by about 8.4 bp per quarter ($= -0.0084 \times 0.1 = -0.00084$) or 33.6 bp per year.

To summarize, employing segment rank of Active Share level to proxy for level of fund manager confidence, we find a clear inverted U-shaped relationship between confidence level and subsequent performance among mutual fund managers. More specifically, there is a significant positive relationship between Active Share and subsequent performance for mutual funds within the middle quintiles of Active Share while a negative and significant relationship for funds within the top quintile of Active Share. Such inverted U-shaped relationship is confirmed by estimating regressions of subsequent performance on decile dummy variables of the level Active Share and estimating quadratic relationship between Active Share and subsequent performance. Furthermore, a negative relationship between changes in Active Share and subsequent performance is found. Overall, these results provide strong evidence that excessive overconfidence is associated with diminished future performance.

### 6.3 Overconfidence and Subsequent Fund Risk

The results thus far show that mutual fund manager overconfidence reflected by extreme high Active Share on average is associated with diminished subsequent performance. It is also interesting to see if extremely high Active Share would result in higher fund risk.

If fund managers are subject to overconfidence, they might be more likely to engage in “irrational” investment strategies that involve sub-optimal portfolio allocation due to their belief in their private information with over-estimated precision. Not only are their aggressive investments more likely to hurt portfolio performance over time but they are also more likely to turn out very poorly in some instances, and very well in other instances, perhaps due to luck. Consequently, such strategies by overconfident managers can be associated with extreme (good or bad) subsequent performance. In other words, very high Active Share may represent an increased chance for potential good performance but, more importantly, it may also come with a significantly higher chance of suffering severe drawdowns and greater levels of downside risk. To investigate this possibility, this paper calculate the measure of performance extremity proposed by Bär, Kempf and Ruenzi (2011) and then applies the piecewise linear regression of measure of performance extremity on the bottom quintile, the middle three quintiles, and the top quintile of segment rank of Active Share. Results are presented in Table 13.

Consistent with our conjecture that overconfidence results in more extreme performance outcomes, we find positive and statistically significant slope coefficients for the bottom quintile, the middle quintiles, and the top quintile of Active Share rank. This shows that the relationship between the segment rank of Active Share and performance extremity is positive. However, the slope coefficient for the top quintile is about more than three times as large as those for the other quintiles, indicating a convex influence of Active Share on performance extremity. Specifically, holding other factors constant, mutual funds with the highest segment rank of Active Share (Rank 1.0) would experience a significant higher performance extremity in the subsequent period than funds at the bottom of the top quintile (Rank 0.8) by about 0.45 ($= 2.267 \times 0.2 = 0.453$).[7] Furthermore, we test whether an increase of Active Share rank is associated with an increase of performance extremity by including the changes in Active Share rank into the piecewise regression. Consistent with our expectation, results in Table 14 show that changes in Active Share rank are positively related with the performance extremity.

Overconfident managers might also choose investment strategies that involve significantly higher idiosyncratic risk exposure and thereby significantly higher performance dispersion. To investigate this possibility, this paper measures performance dispersion by calculating the standard deviations of residuals from four-factor module and then applies the piecewise linear regression of performance dispersion on quintiles of Active Share rank as before. Results in Table 15 show that the standard deviation of performance residuals is positively related with Active Share rank: the sign of coefficients are all positive and statistically significant. More interestingly, the effect is significantly more pronounced among the fund managers who choose to have extremely high Active Share rank than others. The magnitude of the coefficient on the top quintile of Active Share rank is about two (three) times more than the low quintile (middle quintiles). Furthermore, our results from Table 16 show that changes in Active Share rank are positively related with performance dispersion. These findings thus are consistent with the expectation that mutual fund manager overconfidence is associated with greater performance dispersion as a measure of risk.

[7] A similar result is obtained from our quadratic regressions. Estimated coefficients for both the linear and quadratic impact of Active Share to performance extremity are positive and statistically significant.

Overall, we find strong evidence showing that excessive overconfidence comes with dramatically higher fund risk. In particular, extremely high Active Share is associated with significantly extreme performance outcomes (potentially huge downside risks) and dramatically high performance dispersion. Consistent results are found when investigating the impact of changes in Active Share on these risk measures.

### 6.4 Overconfidence and Subsequent Fund Flows

The consensus view from the literature is that fund inflows are positively related with past performance and this relationship is non-linear. However, the literature overlooks the possible response of fund investors to active management or fund manager overconfidence that has been shown to be associated with deteriorated subsequent performance and increasing fund risk. To look at the response of investors to active management, this paper estimates the following regression:

$$Flow_{i,t} = \alpha + \beta_1 ActiveShareRank_{i,t-1} + Controls + \epsilon_{i,t} \quad (9)$$

where $Flow_{i,t}$ denotes the percentage flow for fund i over the period t to t-1; $ActiveShareRank_{i,t-1}$ denotes the normalized segment rank of Active share for fund *i* during time period *t-1* and *t*; $Controls$ is a vector of control variables relating to fund characteristics that determine subsequent investor flows in the literature, including fund age, fund size, expense ratio, turnover rate, and manager tenure. Most importantly, this paper controls for any convex relationship between past performance and investor flows by adding past performance in linear and quadratic terms. Additionally, we include fund family size (natural logarithm of total net assets under management of the funds belonging to the same fund complex), and net total inflows to funds' family and corresponding objective categories. To mitigate the impact of outliers on the estimates, this paper winsorises flow and turnover at the 1% level. This paper also include year dummies to capture any time fixed effects and market segment dummies to control for segment fixed effects, and cluster observations by fund to control for observation dependence.

Table 17 shows that the coefficient on Active Share rank is positive and statistically significant at the 1% level, suggesting that in general investors chase Active Share, holding all other effects constant. This effect of Active Share on inflows is also economically significant. Specifically, a 0.20 higher of segment rank of Active Share attracts about 0.22% more investor flows or 2.71

(0.46) million higher for a fund of average (median) size. However, it is difficult to conclude that this effect of Active Share on future inflows is due to investors' rational or irrational responses to managers' confidence level. In particular, investors may rationally appreciate active management as one of the essential factors that increase the chance of generating excess returns. It is also possible that investors may irrationally chase excessive active management without thinking of the trade-off between the increased profitable opportunities and greater unanticipated risk exposure. High Active Share that is most likely due to managers' overconfidence after their outstanding performance can be easily misunderstood by investors as an indicator of managers' investment skills. If investors irrationally respond to fund manager overconfidence, we should observe a more pronounced positive relationship between high Active Share and investor flows. To test this conjecture, we estimate the relationship between managers' psychological attributes and investor flows by interacting past performance and Active Share in the following regression:

$$Flow_{i,t} = \alpha + \alpha_1 D_{i,t-1}^{Mid} + \alpha_2 D_{i,t-1}^{Top} + (\beta_1 D_{i,t-1}^{Low,Neg} + \beta_2 D_{i,t-1}^{Mid,Neg} + \beta_3 D_{i,t-1}^{Top,Neg} + \beta_4 D_{i,t-1}^{Low,Pos} + \beta_5 D_{i,t-1}^{Mid,Pos} + \beta_6 D_{i,t-1}^{Top,Pos}) Perf_{i,t-1} + Controls + \epsilon_{i,t} \qquad (10)$$

where $D_{i,t-1}^{Mid}$ 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; $D_{i,t-1}^{Top}$ equals to 1 if fund *i* belongs to top quintiles of Active Share from time period *t-1* to *t*, and 0 otherwise. These two dummy variables are used to capture the constant effect of belonging to a specific Active Share quintile on subsequent flows. More importantly, this paper includes the 6 other dummy variables which are Active Share quintiles interacting with past performance to capture the differential investors responses to good (positive) and bad (negative) past performance of mutual funds belonging to the bottom quintile, the three middle quintiles and the top quintile of Active Share. Specifically, $D_{i,t-1}^{Low,Neg}$ equals to 1 if fund *i* belongs to the bottom quintile of Active Share and has negative past performance from time period *t-1* to *t*, and 0 otherwise; $D_{i,t-1}^{Mid,Neg}$ equals to 1 if fund *i* belongs to the three middle quintiles of Active Share and has negative past performance from time period *t-1* to *t*, and 0 otherwise; $D_{i,t-1}^{High,Neg}$ equals to 1 if fund *i* belongs to the top quintile of Active Share and has negative past performance from time period *t-1* to *t*, and 0 otherwise; $D_{i,t-1}^{Low,Pos}$ equals to 1 if fund *i* belongs to the bottom quintile of Active Share and has positive past performance from time period $t$-$1$ to $t$, and 0 otherwise; $D_{i,t-1}^{Mid,Pos}$ equals to 1 if fund $i$ belongs to the three middle quintiles of Active Share and has positive past performance from time period $t$-$1$ to $t$, and 0 otherwise; $D_{i,t-1}^{High,Pos}$ equals to 1 if fund $i$ belongs to the top quintile of Active Share and has positive past performance from time period $t$-$1$ to $t$, and 0 otherwise; and $Controls$ is the vector of control variables relating to fund characteristics defined as in Model (9). All model specifications includes time and segment fixed effect dummies and standard errors are clustered by fund. Results are reported in Table 18.

Consistent with what we find before, investors seem to reward mutual fund managers with higher confidence level as reflected in higher Active Share. The effect however, is mainly driven by the tendency of investors to chase funds with the highest Active Share. The coefficients on the dummy variables for the top quintile of segment rank of Active Share are positive and statistically significant in all model specifications. This effect is also economically meaningful. It suggests that mutual funds belonging to the top quintile of Active Share attract significantly higher investor inflows than those within the bottom quintile of Active Share by about 0.78%. The dummy coefficients for the middle quintiles of Active Share are not statistically significant, meaning that there is no significant difference in subsequent investor flows between the middle quintiles and the bottom quintile, holdings other effects constant.

Looking at the coefficients of the six interaction coefficients, we can observe that cash inflows to mutual funds within the bottom (middle) quintile of Active Share increase about 1.65% (1.97%) for one standard deviation increase of past performance in the prior year when the lagged performance is positive while cash inflows to funds within the top quintile of Active Share increase about 2.63% for on standard deviation increase of prior year performance when the lagged performance is positive. The difference in estimated coefficients between funds within the top quintile and funds with in the bottom quintile (the middle quintiles) of Active Share is statistically significant at the 5% (10%) level, indicating that investors are considerably more sensitive to good performance of fund with high Active Share. The heightened sensitivity to positive returns is also consistent with what we found before that investors appear to chase funds with high Active Share. On the other hand, when mutual funds experience negative past performance, cash outflows from funds within the bottom (middle) quintile of Active Share increase about 1.32% (1.67%) for a one standard deviation decrease of past performance in prior year. Surprisingly, cash outflows from funds within the top quintile of Active Share increase only about 1.37% for a one standard deviation decrease of the prior year performance when the lagged performance is negative. The difference in estimated coefficients are not statistically significant, meaning that investors are similarly sensitive to bad performance among mutual funds with different level of Active Share. The results still hold after controlling for the potential observation dependence by using the Fama - MacBeth (1973) regression. We always find a pronounced asymmetric responses of investors to the past performance of fund with high Active Share relative to non-high Active Share funds.

Overall, our results confirm the non-linear performance-flow relationship documented in the literature (e.g., Sirri and Tufano, 1998), investors chase past mutual fund winners but fail to sell past losers to the same extent. More interestingly, such asymmetric responses of investors to good and poor past performance are significantly more pronounced among funds with high Active Share: there is no pronounced penalty for poor (negative) realized performance but a marked bonus for good (positive) realized returns by overconfident managers. One possible explanation is that investors might interpret the good past performance as the realization of managers' investment skill (perhaps more likely due to luck) and consequently invest disproportionately more into these overconfident managers with high Active Share levels. In contrast, they might view poor past performance of such fund managers as the consequence of bad luck (perhaps more likely due to overconfidence). If this is true, disproportionately high inflows (low outflows) after good (poor) past performance could act as additional confirming market signals to overconfident managers, making these managers are even more likely to attribute successes to their own skills but failures to external factors. As a consequence, overconfident managers are even more likely to overestimate their ability to gather and process information: they revise the precision of their private information upward too much after positive signals from investors' responses and their past success, and put even larger bets on their private information while they inadequately update the precision of their private information downwards too little following negative signals, and fail to put a smaller weight on their private information. This eventually leads to diminished future performance as we observed before.

**7. Conclusions and discussion**

In this paper, we examine overconfidence among mutual fund managers. We investigate whether mutual fund managers are subject to self-serving attribution bias, and whether fund managers become overconfident after good past performance. Using US mutual fund data from 1980 to 2009, we find that fund managers who achieve outstanding past performance choose to have significant higher subsequent Active Share and are more likely to increase Active Share. These findings are consistent with our prediction that superior past performance boosts overconfidence: upon observing successes fund managers overestimate their own skills and put two much weight on their private information which is less precise than they thought. Such biased behavior is significantly more pronounced among solo-managed funds.

Our paper directly relates confidence level to subsequent fund performance. There is strong evidence showing that overconfidence is associated with diminished future performance and increasing fund risk. This result offers one potential explanation for the lack of performance persistence among successful fund managers. Specifically, overconfident managers overestimate the precision of their private information and hence deviate too far from their benchmark indices than they should otherwise, leading to underperformance. Perhaps more interestingly, a closer look reveals a clear inverted U-shaped relationship between confidence level and subsequent performance, consistent with the theoretical model proposed in Shefrin (2009) which illustrates the log-change of a measure corresponding to overconfidence bias.

We also shed new light on the determinants of fund flows by looking at how investors respond to overconfidence of fund managers. Our results suggest that investors irrationally chase overconfident fund managers, flocking to funds with extremely high Active Share when observing good past fund performance but failing to flee from these funds to the same extent following poor fund performance. Such asymmetric reactions from fund investors can serve as another mechanism through which the performance of an overconfident fund managers may suffer: fund managers may become even more overconfident upon observing significant higher fund inflows as confirming market signals for their investment ability.

Further research can extend this paper by including the analysis on Active Share for the period from 2009 to 2015. Since the publication of Cremers and Petajisto (2009), fund investors increasingly view Active Share as an essential indicator of fund mangers' skill and a flawless predictor of fund future performance while fund managers are more aware of the importance of being "active" and might be motivated (or forced) to remain high Active Share in order to attract fund flows. To examine the effect of overconfidence in the context of this paper, our future research will obtain benchmark portfolio holdings and benchmark returns to calculate Active Share and other measures of active management in the literature for all actively managed equity mutual funds from 1980 to 2015. Furthermore, we will also decompose the changes in Active Share into active and passive components, which might be better to capture whether the changes in Active Share is driven by active trading of fund managers or not.

To further investigate the impact of overconfidence on subsequent fund performance and fund flows, researchers can work with other trading behaviors that are commonly used to proxy for overconfidence including portfolio turnover, portfolio concentration, and idiosyncratic risk exposure. In addition, another possible area for further investigation is the demographics factors which influence fund manager overconfidence including education background, experience, location, and gender.

Further work can also explore whether the lack of evidence for superior fund performance in the literature is attributable to excessive overconfidence of fund managers. The consensus view is that on average mutual fund managers fail to outperform their passive benchmarks and the genuine stock selection skill exists only among a small number of fund managers, if at all. On the contrary, recent studies have shown strong evidence of performance persistence in the negative domain, suggesting that poor fund performance is not merely due to bad luck (e.g., Cuthbertson *et al*, 2008). Future research can also identify and understand potential sources of the observed underperformance by overconfident mutual fund managers. Using holding-based performance measures such as Characteristic Selectivity (CS) and Characteristic Timing (CT) performance of Daniel *et al* (1997), we can explore whether overconfident mutual fund managers exhibit poor performance from their stock picking and style timing decisions and directly look at whether overweighed stock holdings in the portfolios managed by overconfident managers represent their "best ideas" or "false beliefs" on their investment ability.

Research evidence suggests that examining trades can be a more powerful method to identify fund manager skills than examining holdings in their portfolios (e.g., Chen, Jagadeesh, and Wermers, 2000; Kothari and Warner, 2001). This is particularly interesting because selling decisions are viewed in the behavioral finance literature to be susceptible to behavioral biases and heuristics. If mutual fund managers become overconfident following outstanding performance, they tend to overestimate their investment abilities and thereby are more likely to form their selling decisions in a much less disciplined way. Future research can explore the relationship between fund manager overconfidence and changes in portfolio holdings and examine differential abilities of overconfident mutual fund managers by decomposing the aggregate performance into different dimensions such as buying and selling components.

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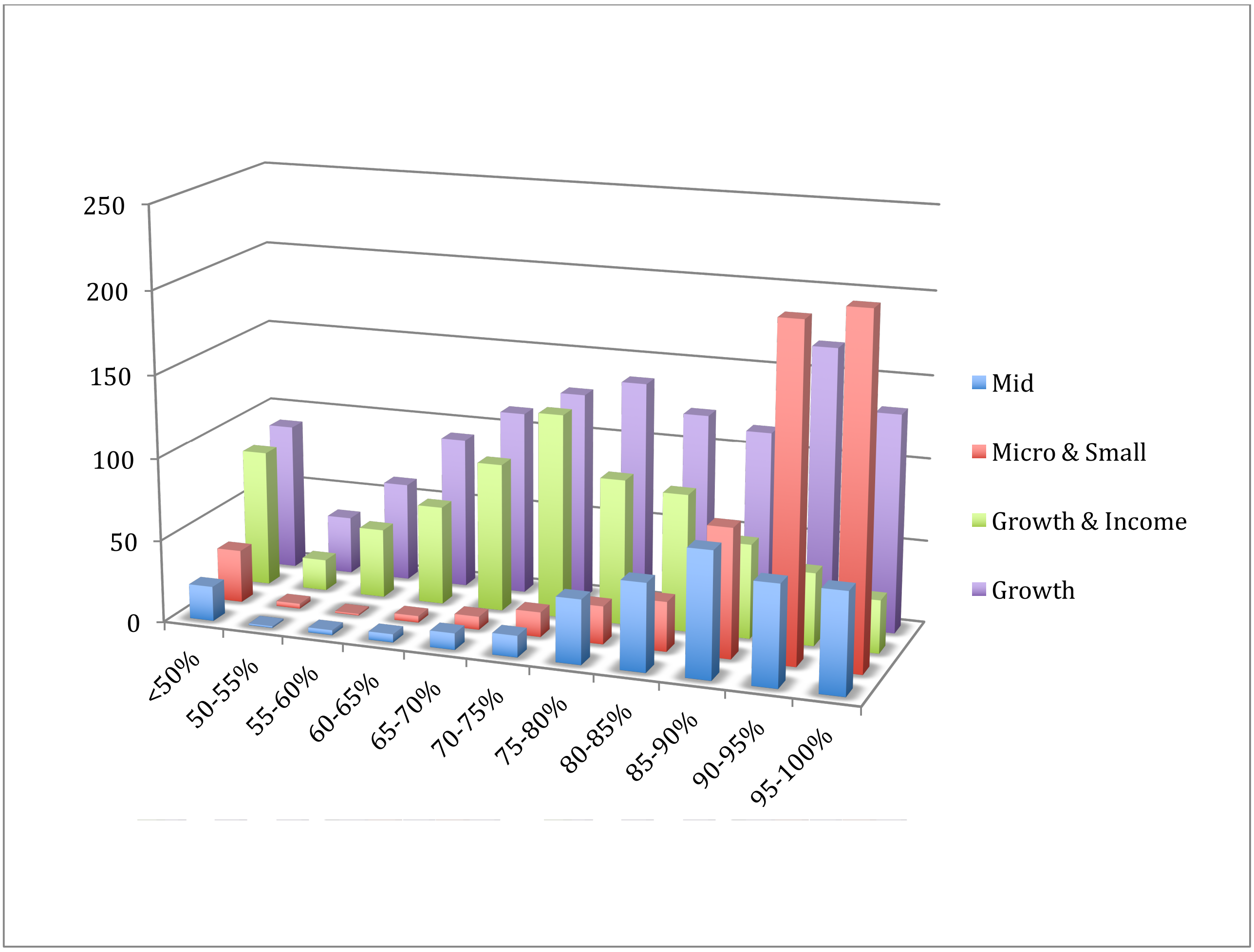
**Figure 1 Number of Mutual Fund in Each Active Share Category, across Investment Objective Segments**

The figure below shows the number of mutual funds in each time series average of Active Share category across four major investment objective segments including Micro-cap and Small-cap funds, Mid-cap funds, Growth funds, and Growth & Income and Income funds.



## Table 1 Descriptive Statistics of Mutual Fund Samples

The table below 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. Avg TNA is the average of total net assets under management of mutual funds in million dollar. Avg Turnover is the cross-sectional average of mutual fund turnover ratio. Avg Exp is cross-sectional average expense ratio of mutual funds. Avg Active Share is the cross-sectional average 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 summary statistics of all mutual fund samples over time and Panel B reports the summary statistics of mutual fund with different investment objectives.

| Year | Number of Funds | Avg TNA | Median TNA | Avg Exp Ratio | Avg Turnover | Avg Active Share |
|---|---|---|---|---|---|---|
| *Panel A Summary statistics of all mutual fund samples over time* | | | | | | |
| 1980 | 105 | 195.05 | 72.90 | 0.98% | 82.91% | 90.55% |
| 1985 | 159 | 323.50 | 150.97 | 1.03% | 80.79% | 90.53% |
| 1990 | 323 | 460.69 | 146.22 | 1.20% | 81.18% | 81.69% |
| 1995 | 794 | 931.49 | 212.59 | 1.20% | 81.42% | 78.72% |
| 2000 | 1354 | 1465.24 | 250.25 | 1.24% | 97.95% | 72.06% |
| 2005 | 1540 | 1549.72 | 252.05 | 1.26% | 82.87% | 74.97% |
| 2009 | 1287 | 1591.50 | 278.40 | 1.18% | 94.60% | 74.01% |
| *Panel B Summary statistics of mutual fund with different investment objectives* | | | | | | |
| Micro-Cap | 38 | 304.01 | 131.80 | 1.62% | 108.62% | 95.12% |
| Small-Cap | 592 | 653.49 | 213.42 | 1.32% | 98.95% | 84.83% |
| Mid-Cap | 342 | 845.69 | 219.90 | 1.26% | 115.20% | 78.28% |
| Growth | 1296 | 1296.47 | 195.92 | 1.21% | 88.61% | 75.57% |
| Growth&Income | 612 | 1957.11 | 263.31 | 1.11% | 64.86% | 67.45% |
| Income | 126 | 1625.05 | 284.10 | 1.17% | 57.52% | 71.29% |

## Table 2 Summary Statistics of Active Share

This table below presents the summary statistics of Active Share across funds' self-report investment objectives including Growth, Growth & Income, Income, Micro-Cap, Small-Cap, and Mid-Cap. The investment objectives codes are defined and obtained from the merged CRSP mutual fund holdings databases. 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.

| Objective Categories | Mean | Std Dev | Minimum | Lower Quartile | Median | Upper Quartile | Maximum |
|---|---|---|---|---|---|---|---|
| Micro-Cap | 95.12% | 6.03% | 57.13% | 94.67% | 97.04% | 98.30% | 99.89% |
| Small-Cap | 84.83% | 20.00% | 0.00% | 85.06% | 91.23% | 94.76% | 99.76% |
| Mid-Cap | 78.28% | 21.89% | 0.00% | 75.04% | 85.05% | 90.86% | 98.73% |
| Growth | 75.57% | 17.79% | 0.42% | 65.45% | 78.49% | 89.65% | 100.00% |
| Growth&Income | 67.45% | 19.64% | 0.00% | 59.25% | 70.53% | 80.23% | 100.00% |
| Income | 71.28% | 23.83% | 23.83% | 63.34% | 71.04% | 79.26% | 98.09% |

## Table 3 Past Performance and Active Share

The dependent variable is Active Share for each fund-quarter observation. Past performance of mutual fund is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| Past Performance | 0.577*** | 1.111*** | 1.101*** |
| | (3.54) | (7.54) | (7.09) |
| Fund Size | | -0.007 | -0.009 |
| | | (-3.12) | (-3.46) |
| Fund Age | | 0.025 | 0.015 |
| | | (6.52) | (3.43) |
| Expense | | 15.174 | 13.876 |
| | | (13.33) | (11.89) |
| Turnover | | -0.006 | -0.002 |
| | | (-1.12) | (-0.35) |
| Tenure | | | 0.027 |
| | | | (7.78) |
| Fund Flow | | | -0.008 |
| | | | (-0.71) |
| Constant | 1.059 | 0.811 | 0.810 |
| | (85.93) | (28.54) | (26.76) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.365 | 0.459 | 0.462 |
| Obs | 63063 | 59553 | 45444 |

## Table 4 Past Performance Rank and Active Share

The dependent variable is Active Share for each fund-quarter observation. Past performance rank is the normalised rank of fund past performance relative to other funds in the same market segment. The past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| Performance Rank | 0.018*** | 0.038*** | 0.037*** |
| | (4.22) | (9.55) | (8.78) |
| Fund Size | | -0.007*** | -0.009*** |
| | | (-3.18) | (-3.52) |
| Fund Age | | 0.026*** | 0.015*** |
| | | (6.60) | (3.49) |
| Expense | | 15.303*** | 14.012*** |
| | | (13.43) | (11.98) |
| Turnover | | -0.005 | -0.001 |
| | | (-1.02) | (-0.26) |
| Tenure | | | 0.026*** |
| | | | (7.77) |
| Fund Flow | | | -0.011 |
| | | | (-0.97) |
| Constant | 1.051*** | 0.792*** | 0.792*** |
| | (84.57) | (27.52) | (25.92) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.365 | 0.460 | 0.463 |
| Obs | 62928 | 59433 | 45345 |

## Table 5 Quintiles of Past Performance Rank and Active Share

The dependent variable is Active Share for each fund-quarter observation. LOW represents the bottom quintile of past performance rank that is measured as the normalised rank of fund past performance relative to other funds in the same market segment. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter $t$. MID represents the three middle quintiles and TOP represents the top quintile of past performance rank. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| LOW | -0.630*** | -0.479*** | -0.432*** |
| | (-19.28) | (-16.16) | (-13.49) |
| MID | 0.002 | 0.024*** | 0.021*** |
| | (0.31) | (3.70) | (2.92) |
| TOP | 0.785*** | 0.637*** | 0.606*** |
| | (22.44) | (23.06) | (19.03) |
| Fund Size | | -0.006** | -0.008*** |
| | | (-2.87) | (-3.24) |
| Fund Age | | 0.025*** | 0.015*** |
| | | (6.78) | (3.60) |
| Expense | | 14.272*** | 13.047*** |
| | | (12.89) | (11.47) |
| Turnover | | -0.008* | -0.004 |
| | | (-1.67) | (-0.87) |
| Tenure | | | 0.024*** |
| | | | (7.41) |
| Fund Flow | | | -0.023** |
| | | | (-2.05) |
| Constant | 1.151*** | 0.888*** | 0.882*** |
| | (91.88) | (32.22) | (29.92) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.402 | 0.482 | 0.483 |
| Obs | 62928 | 59433 | 45345 |

## Table 6 Quadratic Rank of Past Performance and Active Share

The dependent variable is Active Share for each fund-quarter observation. Performance rank represents the the normalised rank of fund past performance relative to other funds in the same market segment. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter $t$. Performance rank squared is the quadratic rank of past performance. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| Performance Rank | -0.596*** | -0.450*** | -0.419*** |
| | (-21.79) | (-22.40) | (-18.97) |
| $(\text{Performance Rank})^2$ | 0.615*** | 0.485*** | 0.454*** |
| | (23.10) | (23.73) | (20.15) |
| Fund Size | | -0.006 | -0.008 |
| | | (-2.86) | (-3.22) |
| Fund Age | | 0.025 | 0.015 |
| | | (6.70) | (3.55) |
| Expense | | 14.180 | 12.967 |
| | | (12.93) | (11.51) |
| Turnover | | -0.008 | -0.004 |
| | | (-1.69) | (-0.90) |
| Tenure | | | 0.024 |
| | | | (7.39) |
| Fund Flow | | | -0.021 |
| | | | (-1.89) |
| Constant | 1.147 | 0.888 | 0.883 |
| | (93.71) | (33.14) | (30.97) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.406 | 0.484 | 0.485 |
| Obs | 62928 | 59433 | 45345 |

## Table 7 Quintiles of Past Performance Rank and Change in Active Share

The dependent variable is changes in Active Share during the previous quarter for each fund-quarter observation. LOW represents the bottom quintile of past performance rank that is measured as the normalised rank of fund past performance relative to other funds in the same market segment. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter $t$. MID represents the three middle quintiles and TOP represents the top quintile of past performance rank. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| LOW | -0.021** | -0.017 | -0.009 |
| | (-2.08) | (-1.56) | (-0.85) |
| MID | -0.001 | 0.001 | -0.001 |
| | (-0.45) | (0.13) | (-0.55) |
| TOP | 0.054*** | 0.051*** | 0.049*** |
| | (5.86) | (5.32) | (5.00) |
| Lag AS | -0.053*** | -0.061*** | -0.053*** |
| | (-13.28) | (-14.00) | (-11.95) |
| Fund Size | | -0.001*** | -0.001*** |
| | | (-5.32) | (-3.54) |
| Fund Age | | 0.002*** | 0.001** |
| | | (4.83) | (2.22) |
| Expense | | 0.848*** | 0.697*** |
| | | (8.22) | (6.50) |
| Turnover | | -0.001 | -0.001 |
| | | (-1.23) | (-1.61) |
| Tenure | | | 0.002*** |
| | | | (2.70) |
| Fund Flow | | | -0.002*** |
| | | | (-2.62) |
| Constant | 0.067*** | 0.064*** | 0.051*** |
| | (11.52) | (9.97) | (8.61) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.06 | 0.07 | 0.07 |
| Obs | 19694 | 18860 | 14042 |

# Table 8 Quintiles of Past Performance Rank and Active Share, Solo vs Team

The dependent variable is Active Share for each fund-quarter observation. Solo denotes the dummy variable equal to 1 if mutual fund *i* is single-managed during the period *t-1* to *t*, and zero otherwise. LOW represents the bottom quintile of past performance rank that is measured as the normalised rank of fund past performance relative to other funds in the same market segment. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. MID represents the three middle quintiles and TOP represents the top quintile of past performance rank. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| Solo | 0.009* | 0.011 | 0.011* |
| | (1.76) | (1.66) | (1.81) |
| Solo LOW | -0.087** | -0.125** | -0.155*** |
| | (-2.28) | (-2.86) | (-3.60) |
| Solo MID | 0.003 | 0.009 | 0.001 |
| | (0.31) | (0.93) | (0.13) |
| Solo TOP | 0.072** | 0.074** | 0.096** |
| | (1.99) | (2.03) | (2.48) |
| LOW | -0.553*** | -0.374*** | -0.319*** |
| | (-13.30) | (-8.56) | (-7.93) |
| MID | -0.006 | 0.009 | 0.012 |
| | (-0.39) | (0.69) | (0.98) |
| TOP | 0.739*** | 0.598*** | 0.536*** |
| | (16.96) | (14.10) | (13.06) |
| Fund Size | | -0.009 | -0.009 |
| | | (-9.04) | (-10.14) |
| Fund Age | | 0.025 | 0.015 |
| | | (15.17) | (9.53) |
| Expense | | 13.538 | 12.637 |
| | | (24.05) | (23.63) |
| Turnover | | -0.005** | -0.001 |
| | | (-2.62) | (-0.46) |
| Tenure | | | 0.025 |
| | | | (17.77) |
| Fund Flow | | | -0.016 |
| | | | (-1.59) |
| Constant | 0.931 | 0.649 | 0.679 |
| | (69.11) | (42.09) | (45.30) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.212 | 0.325 | 0.344 |
| Obs | 58219 | 56323 | 43145 |

## Table 9 Quintiles of Active Share Rank and Subsequent Performance

The dependent variable is cumulated abnormal performance estimated using past monthly fund returns based on the Carhart (1997) four-factor model for fund-quarter observations. LOW represents the bottom quintile of Active Share relative to other funds in the same market segment. MID represents the three middle quintiles and TOP represents the top quintile of Active Share. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| LOW(ActiveShare) | 0.0067** | 0.0054* | 0.0030 |
| | (2.24) | (1.63) | (0.67) |
| MID(ActiveShare) | 0.0021** | 0.0020** | 0.0031** |
| | (2.23) | (2.08) | (2.41) |
| TOP(ActiveShare) | -0.0090* | -0.0097* | -0.0137** |
| | (-1.74) | (-1.76) | (-2.01) |
| Fund Size | | -0.0005 | -0.0005 |
| | | (-4.29) | (-3.79) |
| Fund Age | | 0.0006 | 0.0006 |
| | | (2.89) | (2.04) |
| Expense | | -0.0260 | -0.0265 |
| | | (0.39) | (-0.29) |
| Turnover | | 0.0011 | 0.0014 |
| | | (3.66) | (3.74) |
| Tenure | | | -0.0001 |
| | | | (-0.13) |
| Fund Flow | | | -0.0067 |
| | | | (-2.83) |
| Past Performance | | | -0.0457 |
| | | | (-9.59) |
| Constant | 0.0018 | 0.0023 | 0.0026 |
| | (0.80) | (0.86) | (0.77) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.033 | 0.034 | 0.038 |
| Obs | 61208 | 58112 | 43388 |

## Table 10 Decile Dummies of Active Share and Subsequent Performance

The dependent variable is cumulated abnormal performance estimated using past monthly fund returns based on the Carhart (1997) four-factor model for fund-quarter observations. The expression $Dummy_n$ indicates whether the fund *i* belongs to the segment rank decile *n* according to its Active Share level during the period of time $t$-$1$ to $t$. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| $Dummy_2$ | 0.0010* | 0.0008 | 0.0004 |
| | (1.71) | (1.38) | (0.61) |
| $Dummy_3$ | 0.0008 | 0.0007 | 0.0009 |
| | (1.40) | (1.03) | (1.11) |
| $Dummy_4$ | 0.0017** | 0.0016** | 0.0013 |
| | (2.55) | (2.29) | (1.51) |
| $Dummy_5$ | 0.0011* | 0.0008 | 0.0005 |
| | (1.65) | (1.26) | (0.62) |
| $Dummy_6$ | 0.0022*** | 0.0020** | 0.0021** |
| | (3.25) | (2.88) | (2.36) |
| $Dummy_7$ | 0.0029*** | 0.0028*** | 0.0028*** |
| | (4.50) | (3.96) | (3.10) |
| $Dummy_8$ | 0.0019** | 0.0018** | 0.0019* |
| | (2.55) | (2.35) | (1.91) |
| $Dummy_9$ | 0.0016** | 0.0013 | 0.0020** |
| | (2.36) | (1.61) | (1.99) |
| $Dummy_{10}$ | 0.0009 | 0.0008 | 0.0001 |
| | (1.16) | (1.00) | (0.16) |
| Fund Size | | -0.0004 | -0.0005 |
| | | (-3.85) | (-3.47) |
| Fund Age | | 0.0006 | 0.0006 |
| | | (2.71) | (1.97) |
| Expense | | -0.0459 | -0.0450 |
| | | (-0.68) | (-0.49) |
| Turnover | | 0.0011 | 0.0015 |
| | | (3.86) | (3.88) |
| Tenure | | | 0.0001 |
| | | | (0.21) |
| Fund Flow | | | -0.0044 |
| | | | (-1.72) |
| Past Performance | | | -0.0441 |
| | | | (-8.69) |
| Constant | 0.0021 | 0.0023 | 0.0022 |
| | (0.91) | (0.87) | (0.67) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.033 | 0.035 | 0.038 |
| Obs | 62934 | 59475 | 44399 |

## Table 11 Quadratic Active Share Rank and Subsequent Performance

The dependent variable is cumulated abnormal performance estimated using past monthly fund returns based on the Carhart (1997) four-factor model for fund-quarter observations. Active Share rank is the normalised rank of Active Share relative to other funds in the same market segment. Active Share rank Squared is the quadratic term of Active Share rank. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter $t$. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| ActiveShare Rank | 0.0079*** | 0.0076*** | 0.0079*** |
| | (3.90) | (3.42) | (2.70) |
| $(\text{ActiveShare Rank})^2$ | -0.0065*** | -0.0064*** | -0.0065** |
| | (-2.95) | (-2.71) | (-2.14) |
| Fund Size | | -0.0004 | -0.0005 |
| | | (-4.31) | (-3.81) |
| Fund Age | | 0.0006 | 0.0006 |
| | | (2.81) | (1.96) |
| Expense | | -0.0300 | -0.0332 |
| | | (-0.46) | (-0.36) |
| Turnover | | 0.0011 | 0.0014 |
| | | (3.68) | (3.77) |
| Tenure | | | -0.0001 |
| | | | (-0.18) |
| Fund Flow | | | -0.0067 |
| | | | (-2.83) |
| Past Performance | | | -0.0456 |
| | | | (-9.58) |
| Constant | 0.0017 | 0.0021 | 0.0022 |
| | (0.75) | (0.80) | (0.65) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.033 | 0.035 | 0.038 |
| Obs | 61208 | 58112 | 43388 |

## Table 12 Change in Active Share Rank and Subsequent Performance

The dependent variable is cumulated abnormal performance estimated using past monthly fund returns based on the Carhart (1997) four-factor model for fund-quarter observations. $\Delta\, ActiveShare\ Rank$ is changes in the normalised rank of Active Share relative to other funds in the same market segment between two quarters. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter $t$. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| $\Delta\, ActiveShare\ Rank$ | -0.0058** | -0.0057** | -0.0084** |
| | (-2.12) | (-1.96) | (-2.38) |
| LOW(ActiveShare Rank) | | 0.0059* | 0.0033 |
| | | (1.71) | (0.73) |
| MID(ActiveShare Rank) | | 0.0019* | 0.0029** |
| | | (1.91) | (2.25) |
| TOP(ActiveShare Rank) | | -0.0095* | -0.0136** |
| | | (-1.67) | (-1.96) |
| Fund Size | | -0.0005*** | -0.0006*** |
| | | (-4.49) | (-3.99) |
| Fund Age | | 0.0007*** | 0.0007** |
| | | (3.03) | (2.20) |
| Expense | | -0.0241 | -0.0218 |
| | | (-0.36) | (-0.23) |
| Turnover | | 0.0011*** | 0.0014*** |
| | | (3.63) | (3.72) |
| Tenure | | | -0.0001 |
| | | | (-0.12) |
| Fund Flow | | | -0.0066*** |
| | | | (-2.78) |
| Past Perf | | | -0.0476*** |
| | | | (-9.77) |
| Constant | 0.003* | 0.002 | 0.002 |
| | (1.73) | (0.88) | (0.76) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.034 | 0.036 | 0.040 |
| Obs | 60218 | 56490 | 42265 |

## Table 13 Quintiles of Active Share Rank and Performance Extremity

The dependent variable is the absolute difference between a fund's performance and the average performance of all funds in the same market segment. The future performance is the cumulated abnormal performance estimated using past monthly fund returns based on the Carhart (1997) four-factor model for fund-quarter observations. LOW represents the bottom quintile of Active Share relative to other funds in the same market segment. MID represents the three middle quintiles and TOP represents the top quintile of Active Share. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter $t$. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| LOW(ActiveShare Rank) | 1.0964*** | 0.7848*** | 0.7123*** |
| | (8.60) | (5.75) | (4.02) |
| MID(ActiveShare Rank) | 0.6580*** | 0.6240*** | 0.6208*** |
| | (18.52) | (17.72) | (15.58) |
| TOP(ActiveShare Rank) | 2.3777*** | 2.3430*** | 2.2675*** |
| | (10.28) | (10.50) | (9.32) |
| Fund Size | | -0.0078* | -0.0075 |
| | | (-1.73) | (-1.40) |
| Fund Age | | 0.0131 | 0.0072 |
| | | (1.44) | (0.64) |
| Expense | | 10.9872*** | 12.3382*** |
| | | (4.79) | (4.28) |
| Turnover | | 0.0811*** | 0.0922*** |
| | | (8.77) | (8.17) |
| Tenure | | | 0.0262** |
| | | | (2.68) |
| Fund Flow | | | -0.1440** |
| | | | (-2.52) |
| Past Performance | | | 0.1616 |
| | | | (1.14) |
| Constant | 0.5451*** | 0.3751*** | 0.3252*** |
| | (7.79) | (5.03) | (3.48) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.075 | 0.080 | 0.080 |
| Obs | 61208 | 58112 | 43388 |

## Table 14 Change in Active Share Rank and Performance Extremity

The dependent variable is the absolute difference between a fund's performance and the average performance of all funds in the same market segment. The future performance is the cumulated abnormal performance estimated using past monthly fund returns based on the Carhart (1997) four-factor model for fund-quarter observations. $\Delta\, ActiveShare\ Rank$ is changes in the normalised rank of Active Share relative to other funds in the same market segment between two quarters. LOW represents the bottom quintile of Active Share relative to other funds in the same market segment. MID represents the three middle quintiles and TOP represents the top quintile of Active Share. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter $t$. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| $\Delta\, ActiveShare\ Rank$ | 0.1186*** | 0.1374*** | 0.1309** |
| | (2.58) | (2.92) | (2.17) |
| LOW(ActiveShare Rank) | | 0.7844*** | 0.7139*** |
| | | (5.75) | (4.02) |
| MID(ActiveShare Rank) | | 0.6255*** | 0.6218*** |
| | | (17.73) | (15.58) |
| TOP(ActiveShare Rank) | | 2.3362*** | 2.2617*** |
| | | (10.50) | (9.32) |
| Fund Size | | -0.0078* | -0.0076 |
| | | (-1.72) | (-1.40) |
| Fund Age | | 0.0129 | 0.0071 |
| | | (1.41) | (0.62) |
| Expense | | 10.9318*** | 12.2693*** |
| | | (4.76) | (4.25) |
| Turnover | | 0.0812*** | 0.0923*** |
| | | (8.77) | (8.18) |
| Tenure | | | 0.0263*** |
| | | | (2.69) |
| Fund Flow | | | -0.1422** |
| | | | (-2.49) |
| Past Perf | | | 0.1635 |
| | | | (1.15) |
| Constant | 1.0093*** | 0.3758*** | 0.3261*** |
| | (15.59) | (5.04) | (3.49) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.0001 | 0.0820 | 0.0790 |
| Obs | 61867 | 58089 | 43372 |

## Table 15 Quintiles of Active Share Rank and Performance Dispersion

The dependent variable is the standard deviations of residuals from Carhart (1997) four-factor module. $\Delta\ ActiveShare\ Rank$ is changes in the normalised rank of Active Share relative to other funds in the same market segment between two quarters. LOW represents the bottom quintile of Active Share relative to other funds in the same market segment. MID represents the three middle quintiles and TOP represents the top quintile of Active Share. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| LOW(ActiveShare Rank) | 0.0113*** | 0.0078*** | 0.0071*** |
| | (8.94) | (6.11) | (4.50) |
| MID(ActiveShare Rank) | 0.0056*** | 0.0054*** | 0.0053*** |
| | (18.82) | (18.20) | (15.19) |
| TOP(ActiveShare Rank) | 0.0199*** | 0.0194*** | 0.0189*** |
| | (10.31) | (10.40) | (9.14) |
| Fund Size | | -0.0000 | -0.0001 |
| | | (-0.24) | (-1.13) |
| Fund Age | | 0.0001 | 0.0000 |
| | | (1.27) | (0.31) |
| Expense | | 0.1147*** | 0.1219*** |
| | | (5.52) | (4.79) |
| Turnover | | 0.0009*** | 0.0010*** |
| | | (8.87) | (8.37) |
| Tenure | | | 0.0002** |
| | | | (2.11) |
| Fund Flow | | | -0.0016*** |
| | | | (-3.00) |
| Past Perf | | | 0.0246** |
| | | | (2.57) |
| Constant | 0.0096*** | 0.0073*** | 0.0077*** |
| | (11.18) | (8.27) | (7.24) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.2286 | 0.2378 | 0.2280 |
| Obs | 61462 | 58124 | 44263 |

## Table 16 Change in Active Share Rank and Performance Dispersion

The dependent variable is the standard deviations of residuals from Carhart (1997) four-factor module. $\Delta\ ActiveShare\ Rank$ is changes in the normalised rank of Active Share relative to other funds in the same market segment between two quarters. LOW represents the bottom quintile of Active Share relative to other funds in the same market segment. MID represents the three middle quintiles and TOP represents the top quintile of Active Share. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter $t$. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Tenure is calculated as natural logarithm of tenure in years current manager takes over the place. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| $\Delta\ ActiveShare\ Rank$ | 0.0018*** | 0.0020*** | 0.0022*** |
| | (5.27) | (5.48) | (5.05) |
| LOW(ActiveShare Rank) | | 0.0078*** | 0.0069*** |
| | | (6.09) | (4.29) |
| MID(ActiveShare Rank) | | 0.0054*** | 0.0053*** |
| | | (18.27) | (15.19) |
| TOP(ActiveShare Rank) | | 0.0193*** | 0.0188*** |
| | | (10.38) | (9.24) |
| Fund Size | | -0.0000 | -0.0001 |
| | | (-0.22) | (-0.93) |
| Fund Age | | 0.0001 | 0.0000 |
| | | (1.25) | (0.45) |
| Expense | | 0.1146*** | 0.1230*** |
| | | (5.51) | (4.68) |
| Turnover | | 0.0009*** | 0.0009*** |
| | | (8.87) | (7.70) |
| Tenure | | | 0.0001** |
| | | | (2.14) |
| Fund Flow | | | -0.0011* |
| | | | (-1.90) |
| Past Perf | | | 0.0041*** |
| | | | (4.68) |
| Constant | 0.0137*** | 0.0073*** | 0.0076*** |
| | (15.36) | (8.28) | (7.02) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.1678 | 0.2380 | 0.2281 |
| Obs | 62121 | 58101 | 43372 |

## Table 17 Active Share Rank and Subsequent Flows

The dependent variable is cumulated fund flows in percentage. Active Share rank is the normalised rank of Active Share relative to other funds in the same market segment. Active Share rank Squared is the quadratic term of Active Share rank. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter $t$. Performance rank is the normalised rank of fund past performance relative to other funds in the same market segment. Performance rank squared is the quadratic term of performance rank. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Family size is calculated as natural logarithm of total net assets under management of fund complex that the fund belongs to. Family flows and Obj flows are the percentage flows to a fund's family and the market segment, respectively. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | (1) | (2) | (3) |
|---|---|---|---|
| ActiveShare Rank | 0.0179*** | 0.0136*** | 0.0109*** |
| | (9.95) | (4.04) | (3.89) |
| Fund Size | | -0.0008 | -0.0061*** |
| | | (-1.58) | (-8.71) |
| Fund Age | | -0.0220*** | -0.0068*** |
| | | (-20.27) | (-6.54) |
| Expense | | -0.8817*** | -0.2631 |
| | | (-3.69) | (-1.36) |
| Turnover | | 0.0048*** | 0.0019 |
| | | (3.09) | (1.44) |
| Fund Risk | | -0.4108*** | -0.4494*** |
| | | (-2.73) | (-3.81) |
| Performance Rank | | 0.0544*** | 0.0422*** |
| | | (6.13) | (5.36) |
| $(\text{Performance Rank})^2$ | | 0.0375*** | 0.0194** |
| | | (3.89) | (2.34) |
| Family Size | | | 0.0043*** |
| | | | (9.35) |
| Family Flow | | | 0.6378*** |
| | | | (27.78) |
| Obj Flow | | | 0.7268*** |
| | | | (13.28) |
| Past Flow | | | 0.0306*** |
| | | | (10.92) |
| Constant | 0.0210*** | 0.0482*** | -0.0342*** |
| | (3.68) | (4.64) | (-3.82) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.018 | 0.089 | 0.304 |
| Obs | 61462 | 58111 | 49410 |

## Table 18 Active Share Rank, Past Performance and Subsequent Performance

The dependent variable is cumulated fund flows in percentage. $D_{i,t-1}^{Mid}$ equals to one if a fund belongs to the three middle quintiles of Active Share, zero otherwise and $D_{i,t-1}^{High}$ equals to one if a fund belongs to the top quintile of Active Share, zero otherwise. The following six dummy variables are the interaction between the quintiles of Active Share and the sign of past performance. For example, $D_{i,t-1}^{Low,Neg}$ equals to one if a fund belongs to the bottom quintile of Active Share and has negative past performance. Active Share rank is the normalised rank of Active Share relative to other funds in the same market segment. Active Share rank Squared is the quadratic term of Active Share rank. The fund past performance is the estimated alpha based on the Carhart (1997) four-factor model, one year prior to the current quarter *t*. Performance rank is the normalised rank of fund past performance relative to other funds in the same market segment. Performance rank squared is the quadratic term of performance rank. In order to mitigate potential endogeneity problem, this paper lags all other variables by one quarter, except the expenses and turnover ratio which are lagged one year due to data availability. Fund age is measured as natural logarithm of age in years since first offer date. Fund size is natural logarithm of total net assets under management in millions of dollars. Expense ratio and turnover ratio are measured in percentage per year. Family size is calculated as natural logarithm of total net assets under management of fund complex that the fund belongs to. Family flows and Obj flows are the percentage flows to a fund's family and the market segment, respectively. Fund flow is calculated as the ratio of $TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. To mitigate the impact of outliers on the estimates, this paper follows the literature and winsorises Flow and Turnover at 1% level. All regression specifications include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effect. The data are quarterly and cover the period from 1993 to 2009. The t-statistics (in parentheses) are based on standard errors clustered by fund.

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| $D_{i,t-1}^{Mid}$ | -0.0072** | 0.0017 | 0.0011 |
| | (-2.65) | (0.67) | (0.53) |
| $D_{i,t-1}^{Top}$ | 0.0067* | 0.0129*** | 0.0077** |
| | (1.78) | (3.57) | (2.61) |
| $D_{i,t-1}^{Low,Neg} \cdot Perf_{i,t-1}$ | 3.7606*** | 2.7427*** | 1.8894*** |
| | (9.29) | (6.98) | (5.17) |
| $D_{i,t-1}^{Mid,Neg} \cdot Perf_{i,t-1}$ | 3.3713*** | 3.1730*** | 2.3889*** |
| | (17.85) | (17.03) | (13.87) |
| $D_{i,t-1}^{Top,Neg} \cdot Perf_{i,t-1}$ | 3.4355*** | 3.1182*** | 1.9620*** |
| | (13.00) | (10.83) | (7.69) |
| $D_{i,t-1}^{Low,Pos} \cdot Perf_{i,t-1}$ | 4.7337*** | 5.1473*** | 2.3503*** |
| | (7.44) | (8.18) | (4.92) |
| $D_{i,t-1}^{Mid,Pos} \cdot Perf_{i,t-1}$ | 5.1766*** | 4.9334*** | 2.8278*** |
| | (12.24) | (12.67) | (8.32) |
| $D_{i,t-1}^{Top,Pos} \cdot Perf_{i,t-1}$ | 6.6228*** | 6.1121*** | 3.7620*** |
| | (10.54) | (9.89) | (7.50) |
| Fund Size | | -0.0014 | -0.0068 |
| | | (-2.67) | (-9.41) |
| Fund Age | | -0.0224 | -0.0069 |
| | | (-20.58) | (-6.55) |
| Expense | | -1.0660 | -0.4064 |
| | | (-4.40) | (-2.06) |
| Turnover | | 0.0043 | 0.0015 |
| | | (2.89) | (1.17) |
| Fund Risk | | -0.6906 | -0.5792 |
| | | (-4.38) | (-4.60) |
| Family Size | | | 0.0047 |
| | | | (10.05) |
| Family Flow | | | 0.6398 |
| | | | (28.80) |
| Obj Flow | | | 0.7364 |
| | | | (10.98) |
| Past Flow | | | 0.0302 |
| | | | (10.97) |
| Constant | 0.0223 | 0.0907 | -0.0044 |
| | (2.61) | (8.62) | (-0.49) |
| Year | Y | Y | Y |
| Segment | Y | Y | Y |
| R-Square | 0.081 | 0.103 | 0.311 |
| Obs | 62920 | 59473 | 50602 |

## Appendix A

The screening procedure for US domestic equity mutual funds is that funds with the Investment Objective Codes (IOC) of International funds (IOC=1), Municipal Bonds funds (IOC=5), Bond and Preferred funds (IOC=6) and Balanced funds (IOC=7) are excluded. Funds with CRSP policy codes for Canadian and international (C&I), Balanced (Bal), Bonds (Bonds), Preferred stocks (Pfd), Bonds and preferred stocks (B&P), Government securities (GS), Money market fund (MM), and Tax-free money market fund (TFM). After these two screening, this report include funds with Lipper Class codes of, if available, "EIEI", "G", "LCCE", "LCGE", "LCVE", "MCCE", "MCGE", "MCVE", "MLCE", "MLGE", "MLVE", "SCCE", "SCGE", and "SCVE" or with Lipper Objective codes of, if available, "CA", "EI", "G", "GI", "MC", "MR", and "SG". If neither Lipper Class codes nor Lipper Objective codes are available, this paper includes funds with Strategic Insight Objective Code (si_obj_cd) of "AGG", "GMC", "GRI", "GRO", "ING", and "SCG". If Strategic Insight Objective codes are unavailable, then funds with the Wiesenberger Fund Type codes of "G", "G-I", "AGG", "GCI", "GRI", "GRO", "LTG", "MCG", and "SCG". If none of the above objective codes are available, funds with a CS policy are included. If CS policy is not available, this paper excludes funds with average stock holdings less than 80% or more than 105%. After these screening procedure used by Kacperczyk *et al* (2008), a number of additional filtering criteria have to be met. First, this report searches for keywords in the fund full name and excludes funds with keywords of "index", "idx", "S&P", "DFA", "program", "ETF", "exchange traded", "exchange-traded", "target", and target date funds. Second, this report only includes funds with available holdings data from the CRSP Mutual Fund Database and funds in the CRSP Mutual Fund fundno/portno map dataset. Third, following Kacperczyk *et al* (2008) and others, funds that hold less than 10 stocks and that managed asset less than $5 million in previous month are excluded. Forth, following Alexander *et al* (2007), funds that have less than four holdings reports that were each preceded by another report in the previous quarter are excluded from the final sample.