Essays on Mutual Fund Underperformance

by
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Thesis

Submitted to the University of Warwick
for the degree of
Doctor of Philosophy

Warwick Business School
September 2015

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Acknowledgements

I wish to express my profound gratitude and respect to my supervisor, Prof. Richard Taffler, for the invaluable guidance and constant support he gave me during this Ph.D. journey. Without his thoughtful advice and continuous encouragement, this thesis would not have been possible. I can never overstate my appreciation for him, and sincerely hope that we can continue to work together in the future.

I am thankful to my second supervisor, Prof. Alok Kumar, who provided me helpful comments and suggestions. I would like to acknowledge Prof. Richard Taffler and Prof. Alok Kumar for helping me acquire mutual fund data. Equally, I am grateful to Prof. Michael Moore and Prof. Amit Goyal, my PhD examiners, who provided me with valuable feedback and constructive suggestions after carefully reading this thesis.

I am also grateful to Dr. Arman Eshraghi, who provided me with constructive comments and valuable suggestions. I also received helpful advice from Prof. April Klein, Dr Li-Wen Chen, Dr. Tao Li and Mr. Hal Haig. In addition, I am thankful to Dr. Alex Stremme for sharing teaching experience.

I am also thankful for the constant support and help from my friends and colleagues. I am fortunate enough to have them with me during the journey. An incomplete list includes Yao Chen, Linquan Chen, Junjie Liu, Zicheng Lei, Wei Wei, Qi Xu, and colleagues at the Warwick Business School. In particular, I would like to thank Hung Ying Fung and Chunling Xia, whose continuous encouragement and support help me go through the most difficult time.

I will always be indebted to my parents, Shiyang Jin and Dongju Li, for their immeasurable love. I cannot thank them enough for their constant support and warm encouragement. I am grateful to my brother, Wangzuo Jin, whose love gives me the strength to carry on. Last but not least, I am grateful to my beautiful wife, Jie Ma, and my little girl, Luming (Alice) Jin, for making this difficult journey much easier and happier. I dedicate this thesis to my family.

Declaration

I declare that this thesis does not incorporate any material that has been previously submitted for a degree or diploma in any University; and that to the best of my knowledge this thesis does not contain any material previously published or written by another person where due reference is not made in the text. I also declare that this thesis has been composed by myself and that all the work is my own.

Liang Jin

September 2015

Abstract

This thesis consists of three essays that study mutual fund manager abilities and investment performance. Extant research suggests that mutual fund managers, as a representative group of professional investors, fail to outperform passive benchmarks. My thesis explores potential sources of fund manager underperformance. Specifically, it investigates whether fund managers have "bad" skills that persistently affect fund performance and, in addition, sheds new light on mutual fund underperformance by investigating the prevalence of behavioural biases among fund managers.

My first empirical study examines whether mutual fund managers possess distinct trading skills. By decomposing aggregate characteristic-timing performance into buying and selling components, I show that on average mutual fund managers exhibit positive characteristic-timing ability when buying stocks but negative characteristic-timing ability when selling stocks. Further persistence tests demonstrate that these differential trading skills are not merely due to chance: fund managers who exhibit superior characteristic-timing performance when buying stocks continue performing buying tasks well, while those who were poor performers in selling tend to underperform in the selling domain in the future. These results suggest that the lack of evidence of timing ability in the literature masks the distinct trading abilities that fund managers really possess. Moreover, using changes in portfolio style along size, book-to-market, and momentum dimensions (i.e., active style drift) as a proxy for strength of conviction, my analysis reveals an inverted U-shaped relationship between fund manager conviction and subsequent characteristic-timing performance. In particular, when fund managers engage aggressively in active style drift, their poor selling ability is overwhelming, leading to negative aggregate performance.

My second study advances my investigation of fund performance and trading skills by considering the fact that fund managers are often forced to trade in response to investor flows. I find strong support for the hypothesis that the liquidity provision imposes significant indirect trading costs on mutual funds. Fund managers exhibit negative characteristic-timing performance only when they experience significant fund inflows. By conditioning fund trades on the direction and magnitude of fund flows, my results are consistent with the theoretical predictions that liquidity-driven trades

underperform valuation-motivated trades. In particular, fund managers making purely valuation-motivated purchases generate significant characteristic-timing performance but are not able to do so when compelled to work off excess cash from investor inflows. Fund managers are not able to produce characteristic-timing returns from their selling decisions, even when they are highly motivated by valuation beliefs. Further results reveal that fund managers who possess superior selling ability are also significantly better at buying stocks than the remaining funds and as a result, these fund managers exhibit significant higher aggregate characteristic-timing returns. Strikingly, fund managers who appear to buy stocks well are not able to outperform other funds when selling stocks and they exhibit no significant aggregate performance. Overall, these results highlight and reinforce the insight that fund managers have positive buying skill and negative selling skill.

My final empirical study explores the effect of overconfidence on actively managed equity mutual fund managers. Using the sum of absolute deviations from the fund's benchmark index (i.e., Active Share) as a proxy for confidence level, my results show that fund managers tend to boost their confidence after outstanding past performance: they are more likely to increase Active Share and also choose a much higher Active Share level. Such bias is more pronounced among solo-managed funds than team-managed funds. More importantly, I uncover an inverted U-shaped relationship between confidence level and subsequent performance. In particular, excessive overconfidence, as reflected in an extremely high level of Active Share, is associated with diminished future fund performance, as well as more extreme performance outcomes and greater performance dispersion. I further document irrational investor reaction to fund manager overconfidence. There is a marked bonus for good performance by overconfident managers, as rewarded by higher fund inflows, while there is no pronounced penalty for poor performance, compared to other funds with comparable performance. Investors are not averse to overconfident fund managers even if they lose them money!

Abbreviation

AMEX American Stock Exchange

AS Average Style

ASD Active Style Drift

AVG Average

BF Buy Flow Score

btm Book-to-Market Ratio

CAPM Capital Asset Pricing Model

CFA Chartered Financial Analyst

CRSP Center for Rsearch in Security Prices

CS Characteristic-Selection

CT Characteristic-Timing

EU Expected Utility

EW Equally-Weighted

Exp Fund Expense Ratio

HML High Minus Low (Value Premium)

LOW Bottom Quintile

MFLINKS Mutual Fund Links Database

MID Three Middle Quintile

mom Momentum

MOM Momentum

NASDAQ National Association of Securities Dealers Automated Quotations

NAV Net Assets Value

NBER National Bureau of Economic Research

Neg Dummy Variable for Negative Fund Performance

NF Net Fund Flows

NYSE New York Stock Exchange

Obj Mutual Fund Investment Objective

Obs Observation

Perf Fund Performance

PerfRank Fund Performance Rank

Pos Dummy Variable for Positive Fund Performance

PSD Passive Style Drift

PSN Plan Sponsor Network

RET Fund Return

SD Style Drift

SEC U.S. Securities and Exchange Commission

SF Sell Flow Score

SMB Small Minus Big (Size Premium)

Std Dev Standard Deviation

TNA Total Net Assets

TOP Top Quinitle

TSD Total Style Drift

VW Value-Weighted

WRDS Wharton Research Data Services

Chapter 1

Introduction

1.1 Mutual Fund Underperformance

There has been tremendous and persistent growth in the mutual fund industry over the last three decades. According to the Investment Company Fact Book (2015),[1] total assets under mutual fund management in the U.S. market reached nearly $16 trillion by the end of 2014, making it one of the largest financial intermediaries in the United States.[2] Assets under management are almost 120 times the $135 billion the industry managed in 1980. In 2014, more than 53 million households (43%) owned mutual funds, with a median household investing of $103,000. Mutual funds were managing about 24 percent of total household financial assets and owned more than 30 percent of total corporate equity in U.S. market.

While these is no doubt that mutual funds play a key role in financial system, whether fund managers have the skill or talent to deliver exceptional returns to fund investors still remains unclear. In fact, a significant body of literature on mutual fund performance finds that on average actively managed mutual funds fail to outperform passive benchmarks, net of fees and after controlling for differences in systematic risk exposure.[3] This negative average abnormal performance indicates that mutual fund managers as a group don't have special ability to pick stocks that deliver superior

[1] Source: Investment Company Fact Book 2015 (https://www.ici.org/pdf/2015_factbook.pdf).
[2] Note that equity funds make up 52% of the total assets managed by mutual funds and a significant portion of this amount is actively managed.
[3] See e.g, Lakonishok *et al* (1992), Grinblatt *et al* (1995), Daniel *et al* (1997), Carhart, (1997), Chevalier and Ellison (1999), Wermers (2000), Baks *et al* (2001), and Pástor and Stambaugh, (2002) and others.

returns. This disheartening finding of mutual fund underperformance is not improved upon with recent market timing studies, many of which document a perverse tendency of mutual fund managers to negatively time the market and suggest that fund managers tend to increase market exposure when market returns are low.[4] Using more sophisticated timing measures, recent studies such as Ferson and Schadt (1996), Becker *et al* (1999) and Jiang (2003) still fail to provide convincing evidence to show that fund managers have superior market-timing ability.

These findings, if they were true, would be troubling from an economic point of view. There should be no reason to reward fund managers who cannot beat the market consistently or only produce superior performance by luck. Yet, in reality, fund investors seem to neglect mutual fund underperformance and continue to invest their money in actively managed mutual funds paying significant amounts in management fees and expenses searching for superior returns. A recent study conducted by French (2008) shows that on average investors spend 0.67% of the aggregate market value of all NYSE, AMEX, and NASDAQ stocks each year on the costs of active investing. In other words, the typical investors would earn about 67 basis points more each year by simply switching to a passive market portfolio investing strategy.

Why do mutual fund managers underperform? The answer is not that simple. Sharpe (1991) and Fama and French (2010) argue that average actively managed mutual fund cannot outperform average passively managed funds. That is because, although some active investors have positive returns at the expense of other investors and, after the costs of active investing, on average the net returns to investors must be a negative sum game. Fama and French (2010) re-examine the performance of individual mutual

[4] See e.g., Treynor and Mazuy (1966), Chang and Lewellen (1984), and Henriksson (1984) and others.

funds by using bootstrap simulations to separate skill from luck. The authors conclude that the majority of fund managers do not have specially skills or talents and only a few, if any, fund managers can outperform and cover the cost of active investing.

While a number of recent studies find similar results i.e., at best that there only exists a very small subset of mutual fund managers with genuine skills,[5] performance persistence studies show that superior fund performance appears to be largely unpredictable from past performance, and many researchers attribute superior performance to luck rather than skill.[6] Using a rational model, Berk and Green (2004) propose a possible explanation suggesting that abnormal fund returns that might reflect the scarce resource of managerial talent are quickly bid way in a competitive market: fund managers with skills and superior past performance will attract significant fund inflows, leading to increasing operational scale, marginal costs to active management and, eventually a lack of superior performance persistence. However, the competitive model of Berk and Green (2004) is not able to explain the performance persistence in the negative domain. Recent studies such as Kosowski *et al* (2006), Barras *et al* (2010), and Cuthbertson *et al* (2008) find that evidence of persistence among loser funds, but not among winner funds. In particular, Cuthbertson *et al* (2008) suggest that the inferior performance of most poorly performing funds is not merely due to bad luck, but instead most of them exhibit "bad skill". It is particularly puzzling that most funds in the left tail of the performance distribution manage to survive in a competitive market. Cuthbertson *et al* (2008) conjecture that

[5] See e.g., Kacperczyk *et al* (2005, 2008), Kacperczyk and Seru (2007), Cremers and Petajisto (2009), Huang *et al* (2011), and Cohen *et al* (2011) and others

[6] See e.g., Grinblatt and Titman (1992), Hendricks *et al* (1993), Brown and Goetzmann (1995), Carhart (1997), Wermers (2003), and Bollen and Busse (2005) and others.

the survival of funds with “bad skill” may be due to information asymmetry, or irrational behavior on the part of fund investors.

Most existing research relies on the CAPM or extended multi-factor models to evaluate mutual fund performance. However, such static analysis to a large extent overlooks the reality that active portfolio management is a dynamic process (Admati *et al*, 1986; Ferson and Schadt, 1996; Becker *et al*, 1999; Ferson and Khang, 2002). Moreover, the unobservable nature of risk and the randomness in financial asset returns make it difficult to gauge whether mutual fund managers can deliver exceptional returns to their clients, even if they can do this (Kacperczyk *et al*, 2014). Existing performance measures can falsely attribute performance to uninformed funds, or fail to attribute superior performance to informed funds (Grinblatt and Titman, 1989).

More importantly, traditional finance assumes that the market and its participants are “rational” in theoretical models: they process new information efficiently and update their beliefs correctly, and constantly seek to maximize their expected utility (EU). However, Barberis and Thaler (2003) among others argue that these two underlying assumptions of economic rationality about human behavior are inaccurate. Behavioral finance argues that investors are human beings who are usually susceptible to behavioral biases and heuristics that can negatively affect their investment decisions. Considering the real world of professional asset management where is full of incomplete information and constant and intense competition (Tuckett and Taffler, 2012), behavioral finance allows us to have a better understanding of the trading behavior and performance of investment managers.

This thesis studies mutual fund manager abilities and investment performance. Following the insights of behavioral finance, it aims to explore potential sources of fund manager underperformance widely documented in the literature. Relying on behavioral finance to provide the underlying theory and help explain for the reason why sell decisions are particularly susceptible to behavioral bias, my first two studies aim to provide reasons for the lack of evidence of overall characteristic-timing performance documented in the literature. Specifically, the second chapter of this thesis disaggregates extant research looking at whether fund managers or subsets of fund managers have characteristic-timing skill in terms of subsequent aggregate returns by breaking down such overall investment skill into its different components such as buying and selling skills. The third chapter advances the investigation of distinct skills by relating trade performance to fund manager motivations and explores the possibility of whether different groups of fund managers have different trading skills. The fourth chapter sets out to directly explore whether behavioral biases could play an important role in explaining mutual fund underperformance. Specifically, it investigates whether professional investors such as mutual fund managers are prone to self-serving attribution bias and overconfidence and, more importantly, whether and how these behavioral biases affect subsequent fund performance and fund flows. The following two sections present more detailed introductions to my research questions.

1.2 Fund Manager Bad Skills

A conventional belief has developed in the academic community that mutual fund managers, as a representative and important group of professional investors, have no special ability to time the market as a whole or separate risk factors. For instance, earlier empirical studies such as Treynor and Mazuy (1966), Chang and Lewellen

(1984), Henriksson (1984) and others show that significant market timing ability is rare among mutual fund managers. The most puzzling aspect of the empirical evidence in most of these studies is that average market timing performance across mutual funds is negative and that mutual fund managers who exhibit superior market timing ability show negative performance more often than positive performance. This suggests that the typical fund manager tends to increase market exposure when stock returns are low, which has been interpreted as "perverse market timing" ability in the literature. Using more sophisticated tests, more recent studies such as Becker *et al* (1999), Jiang (2003), Elton *et al* (2012) and others still fail to find convincing evidence that funds have superior market-timing ability.

One possible reason for this unfavourable view of fund manager timing ability is that extant work on timing ability has concentrated on investigating whether mutual fund managers or a subset of them have timing ability by testing the market timing performance in aggregate which might not necessarily be a good indicator of the timing skills mutual fund managers really possess. The possibility that mutual fund managers may be good at some tasks but bad at the other tasks, such as buying and/or selling abilities may therefore be overlooked.

The investment community tends to put most emphasis on decisions relating to how and when to buy stocks. The finance literature equally focuses mainly on buy decisions and various valuation methods and stock investment styles in the buy domain have been rigorously investigated and empirically tested in prior work. On the other hand, sell decisions, which are essential to capture all the performance produced from buy decisions in the investing process, have received relatively infrequent mention in the practitioner literature, and academic journals have tended to remain silent on this issue (Faugere *et al*, 2004).

Sell decisions are assumed in traditional finance literature to be other side of the same coin to buy decisions. However, in practice they are far less disciplined than buy decisions and, as a result, are more prone to behavioural influences, compared with buy decisions. The behavioural finance literature recognizes the existence of differential investment behaviours and explains how sell decisions are more likely to be susceptible to behavioural biases and heuristics. It suggests that buy decisions may be more forward looking in terms of prospective performance while sell decisions may be more backward looking focusing on past performance. For instance, several studies of selling behavior in natural and experimental markets provide evidence that investors are more reluctant to realize losses than gains (Odean, 1998; Weber and Camerer, 1998). Shefrin and Statman (1985) label this phenomenon the "disposition effect". Working with a discount brokerage database, Odean (1998) finds that retail investors tend to selling winning stocks rather than losing stocks using the original purchase price as a reference point. A similar pattern can also be found in other markets such as the housing market (Genesove and Mayer, 2001). Genesove and Mayer (2001) show that house sellers tend to set an asking price that exceeds the asking price of other sellers with comparable houses when the expected selling price is below their original purchase price. On the other hand, behavioural biases can lead to the opposite selling phenomenon that investors tend to hold winners too long before selling them. One of the behavioural explanations is the "endowment effect", a tendency for people to hold on to what they already possess rather than to exchange for a better alternative (Knez *et al*, 1985; Kahneman *et al*, 1991). Barberis and Thaler (2003) argue that the endowment effect is associated with loss aversion and regret aversion.

A survey conducted by Cabot Research and the CFA Institute provides direct evidence that mutual fund managers have to rely on subjective judgment to shape their sell decisions, rather than more quantitative or research based methods (Cabot Research, 2007). In particular, more than 80% of participants in their survey indicate that judgment plays an important role in making sell decisions and over 70% of the respondents indicate that their decisions are formed from experience, trial and error, and advice from past mentors.

If there is more skill required in selling stocks in it not being possible to make similar highly disciplined decisions as in the buy domain, mutual fund managers who have to make buy and sell decisions in their everyday career might not exhibit overall characteristic-timing skill but have differential characteristic-timing abilities for buying and selling. In this scenario, the lack of evidence of overall mutual fund performance along the market-timing and characteristic-timing dimension documented in the literature might mask the existence of positive buying but negative selling skills.

Chapter 2 decomposes aggregate fund characteristic-timing performance into different components such as buying and selling and investigates whether fund managers have distinct trading skills. Using the CRSP Mutual Fund Holdings Dataset with a broad sample of 3384 unique U.S. actively managed domestic equity funds from September 2003 to December 2013, I find that mutual fund managers possess distinct trading abilities. In particular, mutual fund managers on average earn characteristic-timing returns of 1.42% per year when adding stocks into their portfolios, indicating that fund managers possess abilities in the buy domain. However, fund managers exhibit no characteristic-timing skill when selling stocks. Instead, selling decisions are associated with negative characteristic-timing returns of -1.78% per year, significant at the 5% level.

Chapter 2 also aims to examine whether characteristic timing abilities persist over time by sorting mutual fund portfolios into quintiles based on their past characteristic-timing performance and then tracking the future performance of each performance quintile. I find strong persistence of aggregate characteristic-timing performance in the negative domain, at least over the following four quarters, suggesting that mutual fund managers do not possess characteristic-timing ability in aggregate but instead a subset of fund managers tend to have poor timing ability that persistently hurts their overall portfolio performance. Furthermore, my results reveal that fund managers who exhibit superior characteristic-timing performance when buying stocks in the past tend to continue performing buying tasks well in the near term, while those who were the worst performers for selling stocks tend to underperform in the selling domain over the following quarter. In other words, a small number of mutual fund managers have “hot” hands in buying stocks, while another subset of fund managers have “icy” hands in selling stocks in the short term. Any extreme negative (positive) performance for buying (selling) is due to bad (good) luck.

By using the absolute changes in portfolio style (i.e., active style drift) of Wermers (2012) as a proxy for fund manager conviction, preliminary tests in Chapter 2 examine the relationship between fund manager conviction and subsequent characteristic-timing performance. If mutual fund managers are skilled, strong fund manager conviction, as reflected in large style changes in their portfolios, should be associated with superior subsequent characteristic-timing performance. However, a non-linear relationship might exist because large active style drift might, at least partly, result from other factors, rather than valuation beliefs, such as overconfident.

Indeed, an inverted U-shaped relationship between fund manager conviction and subsequent characteristic-timing performance is observed. In particular, strong fund manager conviction as reflected in most aggressive style bets is associated with diminished subsequent characteristic-timing returns, suggesting that there might be more than valuation beliefs in shaping these characteristic-timing decisions. Further, by decomposing aggregate characteristic-timing performance into buying and selling, I investigate the relative performance contributions from buying and selling activities to aggregate performance along different levels of fund manager conviction. My results show that on average strong fund manager conviction is associated with positive but insignificant characteristic-timing performance in the buy domain but strong conviction is associated with statistically and economically significant negative characteristic-timing returns when selling down stocks. In other words, when fund managers engage aggressively in active style drift, their poor selling ability is overwhelming, leading to negative aggregate performance.

Chapter 3 continues the investigation of mutual fund characteristic-timing ability and distinct trading skills by considering the potential adverse impact of investor flows in my performance analysis. There is a large body of literature investigating mutual fund investor behaviours proxied by flows into and out of individual funds. The majority of studies in this literature place emphasis on understanding how individual investors react to certain fund characteristics. In particular, a number of articles have shown that investors seem to irrationally chase fund performance (e.g., Ippolito, 1992, Chevalier and Elison, 1997; and Sirri and Tufano, 1998). The non-linear performance-flow relationship can be used to explain several existing anomalies and puzzles documented in the mutual fund literature (e.g., Gruber, 1996; Chevalier and Elison, 1997; Zheng, 1999; and Frazzini and Lamont, 2006) and asset pricing literature (e.g., Coval and

Stafford, 2007; and Lou, 2012). Surprisingly, less attention has been paid to examining the direct impact of fund flows on fund performance.

Recent studies such as Chordia (1996) and Nanda *et al* (2000) argue that mutual fund managers provide investors with valuation expertise and diversified equity positions at low direct costs for liquidity. When investing on their personal account, individual investors bear the entire liquidity risk. On the other hand, mutual funds are required by law to pay a proportional share of the net asset value of the fund to investors who choose to redeem fund shares. This unique structural design of open-end mutual funds actually allows fund investors to buy and redeem fund shares without paying a large premium for immediate liquidity needs.

However, this provision of low cost liquidity is not "cheap" for fund managers. Instead, it imposes significant indirect trading costs on open-end funds (e.g., Chordia, 1996; Edelen, 1999; and Nanda *et al*, 2000). Fund managers themselves must engage in costly trades in response to significant fund flows. Significant investor inflows can compel fund managers to work off excessive cash by purchasing stocks, even if none of these stocks are believed to be undervalued at the time; similarly, significant investor outflows will constrain fund managers by forcing them to control liquidity in their portfolio by disposing of stocks, even if these stocks are perceived to be under-priced.

In effect, this liquidity-driven trading plays the role of the uninformed trading in the rational expectation models developed in theoretical work such as by Grossman (1976), Hellwig (1980), and Verrecchia (1982). In particular, Grossman and Stiglitz (1980) construct a model in which the market is not perfect: prices do not perfectly reflect the underlying information, so that those who invest resources in collecting information can receive compensation. In such a market, equilibrium can be attained only when liquidity-motivated traders sustain losses to informed traders to compensate the informed traders' cost of information processing. These theoretical studies predict that: first, investors who are forced to engage into a material volume of liquidity-driven trades should experience losses to other informed trades; second, liquidity-driven trades should underperform valuation-motivated trades.

Nevertheless, the majority of previous empirical studies on mutual fund performance neglect the fact that mutual fund managers often have to trade in response to fund flows and these liquidity-driven trades can potentially place fund managers in the role of noise traders. Without controlling for the adverse effect of fund flows, conventional analysis may fail to attribute superior performance to informed fund managers and as a result, provide misleading inference regarding fund managers' skills.

Indeed, Ferson and Schadt (1996) find no evidence of "perverse" market timing when using conditional market timing models that control for time-varying expected market returns. Ferson and Warther (1996) document a positive correlation between aggregate fund flows and lagged instruments for time varying expected market returns, suggesting that fund flows are the source of "perverse" market timing ability. Focusing on individual funds, Edelen (1999) reveals a negative relationship between the volume of liquidity-motivated trading and fund risk-adjusted performance, which questions the common finding of fund manager underperformance in previous studies. Consistent with Ferson and Schadt (1996) and Ferson and Warther (1996), Edelen (1999) finds non-negative market timing performance after controlling for fund flows and concludes that mutual funds exhibit negative market timing performance when and only when they experience fund flows.

The first half of chapter 3 investigates whether mutual fund managers possess market timing ability by considering the adverse impact of fund flows. Unlike Edelen (1999) and others who use the return-based approach, I evaluate timing ability of mutual fund managers by employing the characteristic-timing measure of Daniel *et al* (1997) which uses mutual fund holdings to directly look at whether changes in portfolio weights of three stock characteristics, size, book-to-market, and momentum effect, forecast future returns. This approach not only allows researchers to better capture the dynamic aspects of actively managed portfolios but also avoid the “artificial timing” bias that is usually found in return-based measures. By segmenting fund portfolios based on net investor flows, my analysis shows that mutual fund managers exhibit significantly negative characteristic-timing performance only when they experience significant fund inflows.

Furthermore, I attempt to identify the potential source of this negative timing performance when fund managers experience fund inflows. Specifically, I use the absolute changes in portfolio styles (i.e., active style drift) as a proxy for fund managers’ conviction to make discretionary timing decisions. The rationale is that, when experiencing flow shocks, fund managers can choose to proportionally expand or reduce current stock holdings to maintain their intended risk exposure and control liquidity. Presuming that fund managers have timing ability, they will actively engage in style drift towards the three stock characteristics when and only when they have strong valuation beliefs about future performance. In contrast, my analysis shows that large style bets, which would be expected to be motivated by valuation beliefs, are associated with negative characteristic-timing performance. This suggests that inferior unconditional timing performance is not entirely driven by the detrimental effects of fund flows, but at least partly due to negative timing ability of fund managers.

In the second half of chapter 3, I advance the investigation of fund managers' distinct trading skills and test whether observed differential trading abilities might be driven by the adverse effect of liquidity-motivated trading by relating the performance of mutual fund trades to the motivation for making these trades. Grossman and Stiglitz (1980) and others suggest that uninformed trades should underperform informed trades that represent fund managers' valuation beliefs. Thus, any performance metric that does not account for funds' flow-induced trading can yield negatively biased inferences regarding fund manager ability (e.g., Edelen, 1999). Using unconditional performance, the lack of positive selling performance in Chen *et al* (2013) studies may merely reflect the negative net effect of the cost of liquidity provision and performance of fund managers' selling decisions. In fact, the adverse effect of fund flows on sell decisions can be particularly severe. This is because, when experiencing significant outflows, fund managers without enough cash reserves have no other options available but to sell their assets immediately at fire sale prices (Coval and Stafford, 2007; Zhang, 2010).

A more appropriate indicator of fund managers' skill should be based only on trades motivated by valuation beliefs (e.g., Alexander *et al*, 2007). However fund managers' beliefs are not observable and consequently, the key challenge in the studies on mutual fund performance is to identify ex ante valuation-motivated trades. Cohen *et al* (2011) label each manager's highest estimated alpha holding as his "best idea" and show fund managers' "best idea" generate superior performance. Similarly, Pomorski (2009) shows that when multiple funds in the same fund family trade the same stock in the same direction, that stock outperforms. In order to separate various trading motivations, this chapter follows the approach of Alexander *et al* (2007) to condition trades on the direction and magnitude of concurrent realised net fund flows. The rationale is that fund managers who face severe outflows would buy stocks that are perceived to be significantly undervalued and thus a larger proportion of the purchases they make in their portfolios are likely to be motivated by valuation beliefs. On the other hand, when experiencing significant inflows, fund managers are compelled to work off excess cash, and thus a smaller proportion of the purchases in their portfolios are likely to be valuation-based ones. Symmetrical intuition applies to fund managers' sales of stocks.

My analysis reveals that fund managers making purely valuation-based buys generate significant characteristic-timing performance but are not able to do so when they are compelled to work off excessive cash from investor inflows. On the other hand, fund managers appear to have a "striking" ability to sell stocks at the wrong time. Sales of stocks are associated with negative and significant characteristic-timing returns, even when sells are most likely to be motivated by their valuation beliefs. These results are robust when using multivariate regressions to control other mutual fund characteristics that might be related to the performance of fund trades. Overall, my findings confirm that the observed fund managers' distinct trading skills, in particular negative selling skill, are not driven by the adverse effect of fund flows.

Most studies on mutual fund performance view fund managers as a homogeneous class of professional investors, and to the best of my knowledge, the literature has not yet explored whether different groups of fund managers possess different skills. By identifying the top 25% of funds in terms of their selling (buying) ability, I provide strong evidence to show that, "good sellers" outperform other fund managers when selling stocks by a significant average of 1.35% per year and they also significantly outperform others when purchasing stocks by an average of 0.87% per year. On the other hand, "good buyers" by construction do exhibit good characteristic-timing performance when adding stocks into their portfolios but they are unable to generate superior performance when selling stocks. Furthermore, “good sellers” exhibit a statistically and economically significant outperformance of 0.31% per year in aggregate characteristic-timing performance, while “good buyers” have no significant aggregative performance. These results are consistent with the notion that sell decisions are particularly susceptible to behavioural biases and heuristics, and are not made in a way as disciplined as buying decisions might be. Moreover, my analysis shows that there do exist a small number of skilled fund managers, in particular, those who can manage to make sell decisions in a more disciplined way. These fund managers are likely to possess general investment ability to be able to generate significant outperformance.

To conclude, Chapter 2 and Chapter 3 contribute to the literature on mutual fund performance. I investigate whether mutual fund managers, a representative group of professional investors, exhibit investment abilities, and in particular, whether they possess the skill to time risk factors including the size, book-to-market, and momentum effects. By analysing the changes in portfolio weights of these stock characteristics at the individual stock level, I find no evidence of significant aggregate characteristic-timing skill but instead a strong persistence of aggregate characteristic-timing performance in the negative domain. These results suggest that on average fund managers do not possess characteristic-timing ability in aggregate but a subset of fund managers have poor timing ability that persistently destroys their overall portfolio value.

A number of recent studies such as Edelen (1999) suggest that the perverse tendency of fund managers to negatively time the market is mainly driven by the adverse effect of liquidity-induced trading. After controlling for fund flows, my results show that mutual fund managers appear to have significantly negative characteristic-timing performance when and only when they experience investor inflows. Further investigation reveals that when experiencing fund flows, large style bets are associated with negative characteristic-timing performance. These results suggest that fund managers are not able to make use of the financial flexibility provided by fund inflows, but instead, excessive cash holdings acts as a significant drag on fund performance.

In an attempt to understand why mutual fund managers fail to time risk factors, I decompose aggregate characteristic-timing performance into buying and selling components. Consistent with Chen *et al* (2013), my results show that on average mutual fund managers appear to exhibit distinct trading abilities. In particular, while on average fund managers are able to generate characteristic-timing returns when buying stocks, they have a "striking" ability to sell stocks at the wrong time. Performance persistence tests confirm that such distinct trading skills are not merely due to chance. Fund managers who are successful in buying stocks tend to continue generating superior characteristic-timing performance when purchasing stocks, while those who are the worst sellers tend to continue to underperform when selling stocks in the near term. Further analysis that controls for fund flows confirm that distinct trading skills are not driven by the adverse effect of liquidity-induced trades. In particular, fund managers appear to exhibit "bad" selling ability, even when most of their sales are motivated by valuation beliefs. More interestingly, I find strong evidence to show that there exist a small subset of fund managers who specialise in making sell decisions (good sellers) who also possess buying skill and exhibit superior aggregate performance. However, fund managers who have the best records of buying performance (good buyers) exhibit negative selling ability and they are not able to outperform others in terms of aggregate characteristic-timing performance.

1.3 Fund Manager Overconfidence

In Chapter 4, I investigate whether and to what extent mutual fund managers are prone to self-serving attribution bias and overconfidence. Overconfidence has been the subject of much research in the recent finance literature. A large number of studies relate 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). There is also an extensive literature investigating the potential impact of overconfidence on investors' investment decisions and trading behaviors in the financial market. These studies show that retail investors are prone to overconfidence bias. For example, retail 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).

Despite the extensive studies examining 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. In particular, due to the fact that mutual fund managers play a dominant role in financial market, analysis of the impact of overconfidence on fund manager behaviours and subsequent fund performance can be of paramount importance, both to the academic literature and the investment industry.

Financial economics predominantly assumes that economic agents behave with extreme rationality. In reality, mutual fund managers are under intense 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 be exceptional and they have to believe that they are exceptional (Tuckett and Taffler, 2012). In the end, investment decisions are often made by relying on subjective judgements and beliefs based on managers' private information which can only be verified with vague and delayed feedback.

Theoretical papers such as Daniel *et al* (1998) and Gervais and Odean (2001) introduce self-serving attribution bias into the standard learning models to explain overconfidence. This bias states that people tend to attribute good (positive) outcomes to their own skills while they blame poor (negative) outcomes to chance (e.g., Hastorf, *et al*, 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 good performance but too little responsibility for poor performance and, eventually leads them to become overconfident. More specifically, in financial markets where fund managers can only observe the quality of their private information through delayed and noisy feedback, they are more likely to overestimate their own abilities and revise the precision of their private information and own beliefs upward too much after good performance, while revising their precision downwards too little after poor performance. These biased judgmental processes would lead managers to accumulate unnecessary confidence in their abilities over time, eventually resulting in excessive overconfidence.

A key challenge for any study of investor overconfidence is to come up with a good measure of overconfidence. The ideal way of measuring overconfidence may be to examine the actual estimates and predictions of investors about their future investment performance. However, when it comes to gauging fund manager overconfidence in the real world, researchers have to rely on personal characteristics that have been found in the psychology literature to be related to overconfidence, such as gender (Lundeberg, *et al*, 1994; and Prince, 1993) or the behaviours of overconfident investors derived from theoretical models. Odean (1998) shows that overconfident investors tend to trade more frequently and take greater risk than rational investor would do. By analyzing retail investors, Barber and Odean (2001) document a positive relationship between overconfidence and portfolio turnover and portfolio risk and Goetzmann and Kumar (2008) show that overconfidence is associated with under-diversification. Puetz and Ruenzi (2011) use portfolio turnover ratio as the main proxy for fund manager overconfidence in their study and find that after good past performance fund managers tend to trade more frequently.

However, the turnover ratio might not be a "clean" overconfidence measure because fund managers often have to trade in response to fund flows. An alternative measure that may be more appropriate for fund managers is Active Share. Active Share, calculated as the sum of absolute deviations from the fund's benchmark index, is introduced as a new measure of active portfolio management by Cremers and Petajisto (2009) to capture the extent to which a portfolio deviates from its benchmark index. On the other hand, it also reflects a fund manager's (over)confidence in his private information. In particular, overconfident fund managers may overweight the precision of their private information and concentrate their holdings in stocks where they believe that they have an information advantage, potentially 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 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.

To investigate whether fund managers are subject to overconfidence bias, chapter 4 employs Active Share as my main proxy for level of confidence, and examines the relationship between past fund performance and fund manager confidence level. Specifically, I structure my analysis using piecewise linear regression, which allows me to separately estimate the differential effect of past performance on Active Share in each of five performance quintiles. By analyzing a large sample of U.S. domestic actively managed equity mutual funds, I find a clear U-shaped non-linear relationship between past performance of mutual funds and their subsequent Active Share level. For fund managers who exhibit performance in the top performance quintile in the previous year, the fund's Active Share positively depends on past performance. The effect is statistically and economically significant. There is also a positive relationship between past performance and subsequent Active Share level among fund managers within the three middle performance quintiles. But the magnitude of the effect is dramatically smaller comparing to the top performance quintile. These results suggest that fund managers tend to choose a higher level of Active Share following their successes and this effect is more pronounced for fund managers with outstanding past performance. Consistently, I observe that the best past performers are more likely to increase their Active Share level following outstanding performance.

On the other hand, fund managers who experience very poor past performance are also more likely to choose high Active Share. One possible explanation is that these poorly performing fund managers may engage in gambling, perhaps in an attempt to raise their positions in the future. Overall, these results strongly support our main hypothesis that good past performance leads to overconfidence as reflected in high Active Share.

Motivated by Bär *et al*, (2011) who investigate the impact of management structure on fund manager behaviors, further tests examine the potential difference in the responses to past performance between solo-managed and team-managed mutual funds. Consistent with the argument that self-attribution bias is likely to be more pronounced among individuals than among teams (Nikolic and Yan, 2014), I find evidence to show that solo-managed funds are more likely to have higher Active Share level following outstanding performance than their team-managed counterpart.

More importantly, Chapter 4 directly examines the potential impact of fund manager overconfidence on subsequent fund 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) are more likely to be driven by managers' private information which might actually much less precise than they think. Such overconfidence-driven actions would lead to sub-optimal portfolio allocation and investment decisions and, eventually lead to reduced performance. In this scenario, we should observe a negative relationship between Active Share levels and subsequent performance among funds belonging to the top Active Share quintile. On the other hand, moderate portfolio deviations from benchmark indices are more likely to reflect a manager's normal appropriate confidence level when compared to the top Active Share quintile. Fund managers with normal confidence levels assess and update their private information in a less biased way and put large weights on their private information and smaller weights on other stocks. On this basis, these well motivated trading activities should lead to realization of profitable opportunities and better portfolio allocation, which eventually generates better performance. If this is true, we should observe a positive relationship between Active Share levels and subsequent fund performance for funds within the four quintile groups below the top quintile.

Consistent with the expectation, I find a clear inverted U-shaped relationship between confidence level and subsequent risk-adjusted fund performance. In particular, these is a positive and statistically significant relationship between confidence level and subsequent fund performance among mutual fund managers belonging to the three middle quintiles of Active Share, suggesting that moderate confidence level generates superior subsequent performance. Strikingly, excessive overconfidence as measured by an extremely high Active Share level relative to all other funds in the same segment is significantly associated with diminished future performance. The effect is economically meaningful: on average overconfident fund managers underperform fund managers with normal confidence levels by 27.58 basis points per quarter or about 1.09% per year. Furthermore, there is a negative and significant relationship between changes in relative level of Active Share and subsequent performance, suggesting that on average increases of Active Share that are most likely driven by overconfidence bias are associated with deteriorated subsequent returns. Additionally, further results show a clear convex relation between confidence level and fund risk including performance extremity and performance dispersion. Excessive overconfidence is associated with more extreme outcome, higher performance dispersion, and therefore a potentially higher downside risk for fund investors.

Finally, chapter 4 sheds new lights on the determinants of fund flows by exploring how investors respond to fund manager overconfidence. In a preliminary analysis, we observe a positive relationship between Active Share and fund flows. However, it is difficult to conclude whether this positive relationship is due to investors' rational or irrational responses to fund managers' confidence level. Investors may rationally appreciate active management as one of the essential factors that increases the chance of generating excess returns. It is also possible that investors irrationally chase excessive active management without thinking of the trade-off between the increase profitable opportunities and greater unanticipated risk exposure.

To deepen the understanding of fund investors' behaviours, I investigate the relationship between fund managers' psychological attributes such as overconfidence and investor flows by interacting past performance and Active Share levels. The results are striking. I find strong evidence to show that cash flows into overconfident fund managers are more sensitive to good fund performance than cash flows into other funds, and that cash outflows are similarly sensitive to poor performance for all fund managers. In other words, there is a marked bonus for good performance of overconfident managers, as rewarded by higher fund inflows, while there is no pronounced penalty for poor performance, compared to other funds. I argue that, in financial market with acute information asymmetry, high Active Share, which is most likely to be driven by fund manager overconfidence following their outstanding performance, can be easily misunderstood by investors as an indicator of fund manager's genuine skills. In particular, investors might falsely interpret good past performance of overconfident fund managers as the realization of a fund manager's investment abilities, rather than as a result of luck. On the other hand, investors might attribute poor past performance of these fund managers to chance. As a consequence, investors irrationally chase overconfident fund managers, flocking to funds with extremely high Active Share when observing good fund performance but failing to flee from these funds to the same extent following poor fund performance.

Chapter 4 contributes 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. There are a few related recent studies investigating overconfidence among fund managers. Puetz and Puenzi (2011) report that fund managers trade more excessively after good performance. Similar to my study, Choi and Lou (2010) uses Active Share as a proxy of overconfidence and uses the sum of a series of positive (negative) past portfolio returns as a proxy for confirming (disconfirming) market signals. They find evidence to show 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 (2012) apply content analysis on the reports managers write to their investors and show that mutual fund managers who generate superior past performance become overconfident.

Furthermore, my study is one of the first attempts to directly link fund manager overconfidence and fund performance. The findings that overconfident fund managers overweight their private information, and hence deviate too much from their benchmark, and consequently underperform have important implications for asset pricing and real investment. Moreover, I also document a non-linear relationship between confidence level and future performance, which is consistent with Eshraghi and Taffler (2012).

My study also contributes to the literature regarding the effect of team status by highlighting significant behavioral differences between solo- and team-managed funds. In line with the diversification of opinions hypothesis (e.g., Sah and Stiglitz, 1986, 1991), my results show that solo-managed funds are more likely to be prone to overconfidence and associated self-attribution bias, when compared to team-managed funds. A closely related work by Bär *et al* (2011) documents consistent findings that team-managed funds behave in a less biased way: they exhibit less extreme investment styles, hold less industry concentrated portfolios, and eventually, are less like to experience extreme performance outcomes.

Chapter 4 also contributes to the literature on mutual fund flows. Previous studies (e.g., Ippolito, 1992; Sirri and Tafano, 1998; and Chevalier and Elison, 1997) have shown that investors tend to chase fund past performance. I extend their insight by linking past performance to fund manager confidence level and find that the asymmetric responses to good and poor performance are particularly more pronounced among overconfident fund managers. Investors irrationally chase overconfident fund managers who actually fail to outperform normal confident fund managers in the future. Thus, my findings directly support the “dumb money” effect of Frazzini and Lamont (2008) who show that investors tend to send their money to mutual funds which hold stocks that do poorly in the long run.

Chapter 2

Do Fund Managers Possess Differential Characteristic-Timing Abilities?

2.1 Introduction

Despite the vast amount of resources fund managers expend and the high management fees charged to fund investors, whether fund managers have investment skills or talents to deliver exceptional returns to fund investors still remains unclear. In fact, prior literature on the performance of actively managed mutual funds paints a disheartening picture of active funds on average failing to outperform passive benchmarks and failing to add value for fund investors[1]. In particular, the consensus view is that only a small number of fund managers are able to identify and profit from mispriced stocks[2], if any at all, but little evidence for fund managers' timing ability. Earlier studies such as Treynor and Mazuy (1966), Chang and Lewellen (1984), and Henriksson (1984) suggest that significant market timing ability is rare among mutual fund managers. The most puzzling aspect of the empirical evidence in most of these studies is that the average timing performance across mutual funds is negative and that mutual fund managers who exhibit superior market timing ability show negative performance more often than positive performance. Using more sophisticated tests,

[1] See e.g., Jensen (1968), Friend *et al* (1970), Lehmann and Modest (1987), Elton et al (1993), Malkiel (1995), Carhart (1997), Fama and French (2010) and others.
[2] See e.g., Pástor and Stambaugh (2002), Kacperczyk et al (2005, 2008), Kosowski et al (2006), Cremers and Petajisto (2009), Barras et al (2010), Huang *et al* (2011) and others

more recent studies such as Becker *et al* (1999) and Jiang (2003) still fail to provide convincing evidence that funds have superior market-timing ability.

These studies identify and measure market timing ability by running non-linear regressions of realized fund returns against contemporaneous market returns (return-based measure). One advantage of this return-based approach is the minimal information requirements. Researchers only need information on portfolio and benchmark returns. However, this approach can provide misleading inference regarding market timing ability. First, in the non-linear regression framework, spurious timing can arise due to factors other than active timing strategies of fund managers. Jagannathan and Korajczyk (1986) demonstrate that certain dynamic trading strategies by mutual funds might give rise to a negative non-linear relationship between fund and market returns. These authors also show that the returns of a passive portfolio of certain stocks with option-like payoff structure might also have a convex or concave relation with market returns. Second, most of these studies assume that market timing strategies are implemented in a specific way. Elton *et al* (2012) argue that fund managers might choose to time in a more complicated way. Third, Goetzmann, *et al* (2000) and Bollen and Busse (2001) argue that return-based methods employ monthly return information, and thus ignore the active timing and trading between observations of fund returns, leading to negatively biased timing ability.

To overcome these potential problems of return-based measures, recent studies such as Jiang *et al* (2007) and Kaplan and Sensoy (2008) propose alternative market timing measures based on mutual fund portfolio holdings (holding-based measure). Using a single-index model, these authors find that mutual fund managers have significant timing ability, which is opposite to what has been found in prior return-based studies. However, Elton *et al* (2012) show that the positive timing ability identified by the single-index model turns out to be negative timing ability. Overall, there is also little empirical evidence to suggest that mutual fund managers are able to time the market or exploit time-varying stock characteristics returns.

Extant work has concentrated on investigating whether mutual fund managers possess timing ability by testing the timing performance measured in aggregate. However, aggregate performance might not necessarily be a good indicator of the timing skills that mutual fund managers really possess: mutual fund managers might be able to perform some tasks well, but they might be not good at other tasks. As a result, superior performance from positive skill can be cancelled out by poor performance from negative skill, which perhaps explains the lack of evidence of fund managers' timing skills documented in the literature.

One set of potential candidates for such distinct investment skills consists of buying and selling abilities. Sell decisions are assumed in traditional finance literature to be the other side of the coin to buy decisions, but investment practitioners often find themselves tending to have more trouble with sell decisions than they do with buy decisions. Norris (2002) expresses concern that behavioural and emotional biases can be highly influential in shaping investors' decisions to sell stocks. The author argues that a decision to sell stocks involves changing investors' minds about the prospects of the investments, which can be particularly difficult in the investment world, where investors are swamped with incomplete information. The behavioural finance literature has suggested that sell decisions are susceptible to behavioural biases and heuristics. For example, several earlier studies have shown that retail investors are more likely to sell their winning position but they are reluctant to realise their losses (e.g., Shefrin and Statman, 1985; Odean, 1999). This is known as the "disposition effect". Researchers find that it is very hard to explain the tendency of selling winners over losers in a rational trading framework (e.g., Barberis and Thaler, 2003). On the other hand, a number of behavioural explanations have been suggested such as the concavity (convexity) of the value function in the domain of gains (losses) from prospect theory (e.g., Kahneman and Tversky, 1979).

Interestingly, a recent survey conducted by Cabot Research and CFA Institute shows that mutual fund managers often have to rely on subjective judgment to shape their sell decisions, rather than more quantitative or research based methods (Cabot Research, 2007). Motivated by these findings, this chapter follows Chen *et al* (2013) in exploring whether mutual fund managers possess differential trading skills, by decomposing timing ability in aggregate into different components such as buying and selling skills. Chen *et al* (2013) identify distinct trading skills for a small number of "star" growth-oriented mutual fund managers who exhibit significant abnormal fund performance estimated by the Carhart (1997) four-factor model with 36-, 60- and 108-month fund returns history. However, their analysis can be subject to survivorship bias. It is unclear whether their results are generalizable to other mutual funds, particularly those with average and even below-average historical performance. This chapter attempts to complement Chen *et al* (2013)'s findings by investigating whether such distinct buying and selling characteristics-timing abilities exist in a much broader sample of all U.S. domestic actively managed equity funds.

This chapter also contributes to the literature that examines fund manager abilities to time markets by investigating whether distinct characteristic timing abilities persist over time. In particular, if mutual fund managers have differential trading abilities, characteristic-timing performance for buying and selling should remain persistent over time. In other words, past performance would be a good indicator of future performance. However, if differential characteristic-timing abilities for buying and selling are merely due to chance, past superior (poor) performance may not imply superior (poor) performance in the future.

Furthermore, the majority of prior studies explore timing ability by examining total timing performance, which may be misleading concerning fund managers' timing abilities. Since the natural structure of mutual funds can potentially force managers to trade for other reasons including tax management and window dressing, a more accurate indicator of fund manager skills, if any, should be based only on investment decisions made by strong fund manager beliefs or conviction. Using changes in portfolio styles through active trading (i.e., active style drift) of Wermers (2012) as a proxy for fund manager conviction, this chapter attempts to explore the relationship between the strength of fund manager conviction and subsequent characteristic-timing performance. If mutual fund managers are truly skilled in timing stock characteristics, strong conviction, as reflected in large active style changes in allocation toward equity style factors in the portfolios, should be associated with good subsequent characteristic-timing performance. However, if large active style drifts were made due to factors such overconfidence or gambling behaviour, such active trading decisions can be associated with poor subsequent characteristic-timing returns.

Using the CRSP Mutual Fund Holdings Dataset with a broad sample of 3384 unique U.S. actively managed domestic equity funds from September 2003 to December 2013, I find no evidence of superior stock picking performance in general which is consistent with the literature. In particular, I analyse how changes in portfolio holdings weights of size, book-to-market, and momentum factors at the individual stock level might contribute to overall fund performance. Consistent with Daniel *et al* (1997) and others, my results show that on average, mutual fund managers are not able to effectively time the stock characteristics. Sub-period analysis shows that fund managers exhibit negative characteristic-timing ability with an average return of -46 basis points per year at marginal statistically significance level during the second half sub-period from 2009 to 2013. Further results reveal that none of the fund categories shows positive overall characteristic-timing ability in any of the time periods in our study. Income-oriented mutual funds exhibit negative characteristic-timing skills and, in particular, income mutual funds have an average characteristic-timing performance of -1.53% per year, statistically significant at the 1% level, during the second half sub-period. Furthermore, I find that mutual fund managers possess distinct trading abilities. In particular, mutual fund managers on average earn characteristic-timing returns of 1.42% per year when adding stocks into their portfolios, indicating that fund managers possess abilities in the buying domain. However, fund managers exhibit no apparent characteristic-timing skills when selling stocks. Instead, selling decisions are associated with negative characteristic-timing returns of -1.78% per year, significant at the 5% level.

More importantly, by tracking the subsequent characteristic-timing performance of past winners and losers, this chapter finds a strong persistence of aggregate characteristic-timing performance in the negative domain, at least over the following four quarters, suggesting that mutual fund managers do not possess characteristic-timing ability in aggregate but instead a subset of fund managers tend to have poor timing ability that persistently destroys their overall portfolio performance. This chapter also provides evidence that the characteristic-timing performance for both buying and selling dimensions are persistent. In particular, mutual fund managers who exhibit superior characteristic-timing performance when buying stocks in the past tend to continue performing buying tasks well while those who were the worst performers for selling stocks tend to underperform in the selling domain for the following quarter.

In other words, a small number of mutual fund managers have "hot" hands to buy stocks, while another subset of fund managers have "cold" hands to sell stocks in short term.

By segmenting portfolios based on level of active style drift as a proxy for strength of fund manager conviction, my results reveal that aggregate characteristic-timing returns are not positively related to the strength of conviction in style investments. Instead, an inverted U-shaped relationship between fund manager conviction and subsequent characteristic-timing performance is observed. In particular, strong fund manager conviction, as reflected in most aggressive style bets, is associated with diminished subsequent characteristic-timing returns, suggesting that there might be more than valuation beliefs in shaping characteristic-timing decisions. A closer look by breaking down the aggregate characteristic-timing performance into buying and selling components reveals that the characteristic-timing performance when selling stocks is negatively related to the strength of conviction, while a non-linear relationship for buying ability is found. When mutual fund managers aggressively engage in active style drifts, on average stocks purchased are associated with no statistically significant subsequent characteristic-timing performance whereas stocks sold are associated with statistically and economically significant characteristic-timing returns of -2.97% per year, indicating that the poor overall characteristic-timing performance from aggressive style bets are mainly driven by negative selling abilities.

These findings have meaningful implications for investigating fund manager skills and for understanding asset management in the real world. My results directly question the capability of the traditional performance evaluation approaches employed in the literature, which only consider aggregate mutual fund performance to detect fund manager abilities. The lack of evidence of overall fund performance documented in the literature might mask the distinct buying and/or selling skills mutual fund managers really possess. Moreover, this chapter provides strong empirical evidence to support the hypothesis in the behavioural finance that sell decisions are more likely to be susceptible to behavioural biases and heuristics.

More importantly, my findings concerning the relationship between fund manager conviction and subsequent performance raise the question of whether professional investors such as mutual fund managers, who are often assumed to be informed investors in the traditional finance literature, are also prone to behavioural biases and heuristics. Fund managers operate in an environment where they are swamped by incomplete information, are subject to acute information asymmetry and are under intense competition. In the end, they often have to rely on subjective judgment, intuition and even “gut feeling”, which can easily expose mutual fund managers to behavioural and emotional biases (Tuckett and Taffler, 2012). Surprisingly, little attention in the academic literature has been paid to looking at behavioural biases among professional investors. One notable exception is Eshraghi and Taffler (2012), who provide evidence showing that overconfidence, one of the best known psychological attributes that can play havoc with decision making, is associated with diminished investment performance. However, the fundamental questions about how and through which mechanisms overconfidence can affect fund performance remain unclear. It is possible, for example, that negative selling ability can to a large extent drive the poor performance of overconfident fund managers because the behavioural and emotional factors tend to become even more severe when it comes to sell decisions that involves changing established beliefs on current holdings (Norris, 2002).

The remainder of this study is organized as follows. Section 2.2 summarizes the related literature on mutual fund timing ability. Section 2.3 describes the performance and fund manager conviction measurements used in this chapter. Section 2.4 describes the data source and sample construction. Section 2.5 discusses the results and findings and Section 2.6 concludes.

2.2 Literature Review

The vast majority of the studies in the literature have concentrated on stock picking ability by examining how much better a mutual fund manager can perform compared to holding a passive portfolio of stocks with the same risk characteristics[3]. This bulk of the literature ignores whether managers can generate additional performance by timing the market as a whole or timing across subsets of the market. A number of articles argue that if fund managers can forecast market states, this existence of timing ability can lead to incorrect inference about the stock picking skill (e.g., Dybvig and Ross, 1985; Elton *et al*, 2009).

Given the importance of market timing skills, a number of articles explore whether mutual fund managers could actually forecast market states, and therefore take advantage of such predictability in their portfolio decisions. Treynor and Mazuy (1966) argue that if fund managers out-guess market returns, they will hold a greater proportion of the market portfolio when the market return is high and a smaller proportion when the market return is low. The authors add a quadratic term in the CAPM model to test the non-linear relationship between portfolio return and market return. However, they find no evidence that fund managers in their sample have significant timing ability.

[3] See, e.g., Elton *et al* (1996), Gruber (1996), Daniel *et al* (1997), Carhart (1997), Zheng (1999) and others.

Based on the basic model of market timing developed by Merton (1981), Henriksson and Merton (1981) present both parametric and nonparametric tests for the market timing ability of investment managers by assuming that fund managers follow a more qualitative approach to time market according to whether the market return is lower or higher than the risk-free rate. Using these market timing measures, Henriksson (1984) evaluates the market timing performance of 116 open-end mutual funds, and their empirical results do not support the hypothesis that fund managers possess market timing ability. Chang and Lewellen (1984) and Grinblatt and Titman (1988) find similar results.

Given the “perverse” market timing ability found in earlier studies, Ferson and Schadt (1996) argue that the traditional measures are not able to capture the dynamic behaviour of returns. These authors modify the classic market timing models of Treynor and Mazuy (1966) and Henriksson and Merton (1981) to condition on public information and find that negative market timing performance is removed. In addition to incorporating public information, Beck *et al* (1999) further develop conditional market-timing models by considering the fund manager’s risk aversion, and again find no evidence that mutual funds have significant market timing ability.

The market timing measures commonly used in the literature are based on non-linear regressions of realized fund returns against contemporaneous market returns. If there were a non-linear relationship between fund and market returns, this relationship could be induced by factors other than active market timing actions. Jagannathan and Korajczyk (1986) argue that some commonly used dynamic trading strategies may give rise to option-like features in fund returns, which can appear as non-linear relations between fund and market returns. Thus, spurious timing ability may be due to the “dynamic trading” effect. For example, a fund manager who implements a “positive-feedback” strategy increaseing portfolio exposure to market returns after a market run-up would exhibit a positive artificial timing ability. On the other hand, a contrarian manager who decreases his market exposure after a market run-up would have negative artificial timing ability. Furthermore, the “dynamic trading” effect is also related to “interim trading”, which refers to fund trading activities between return observation dates in the literature. Goetzmann, *et al* (2000) use simulations to tests if “interim trading” would cause return-based tests to underestimate the market timing ability of fund managers. They show evidence that when fund managers engage in market timing at a much higher frequency, the traditional return-based models that are based on monthly fund returns can lead to negatively biased results with lower power. Similarly, Bollen and Busse (2001) perform market timing tests using daily fund returns, and find evidence in favour of fund managers’ timing ability for a sample of 230 domestic equity funds.

Also, the “passive timing” effect is documented in previous studies for return-based measures. Jagannathan and Korajczyk (1986) demonstrate that a “passive” convex or concave relationship between fund returns and market returns might occur due to option-like returns of certain stocks, even when fund managers do not actively time the market. This is known as the “passive timing” effect. Together with the “dynamic trading” effect, these two effects are often referred to as ‘artificial timing’ in the literature. In addition, Elton *et al* (2012) argue that if fund managers choose to time in a more complex manner, timing measures based on non-linear relations between fund and market returns may not be able to detect this.

Jiang *et al* (2007) propose alternative market timing measures based on quarterly mutual fund portfolio holdings. These authors estimate the fund beta as the weighted average of the betas of individual stocks in the fund manager’s portfolio, and then investigate the covariance between fund betas and market returns. Jiang *et al* (2007) argue that by using ex ante information on fund portfolio holdings, the holdings-based approach is not affected by subsequent trading activities during the holding period (the "dynamic trading" effect) and it is also not affected by any contemporaneous non-linear relationship between individual stock and market returns (the "passive timing" effect). Using a sample of 2294 actively managed equity mutual funds, Jiang *et al* (2007) show favourable evidence that fund managers exhibit positive market timing ability through active trading, and that the average market timing performance remain positive after controlling for macroeconomic variables. Similarly, Kaplan and Sensoy (2008) find that although fund managers fail to time their benchmark by changing cash holdings in their portfolios, they do exhibit market timing ability. Increases in benchmark beta of fund portfolios are positively associated with future benchmark excess returns.

Following these two studies, Elton *et al* (2012) examine fund managers' timing ability by using several multi-index models, including a two-index model that incorporates bond timing, the Fama-French model with a bond index, the Carhart (1997) four-factor model and a model that considers industry rotations. In addition, the authors use the general methodology of Ferson and Schadt (1996) to condition public information in their timing models. By investigating monthly holdings of 318 funds, Elton *et al* (2012) confirm that there is positive and statistically significant timing ability when using the one-index model, as Jiang *et al* (2007) and Kaplan and Sensoy (2008) do. However, fund managers' timing ability becomes negative when a multi-index model is used. In addition, Elton *et al* (2012) argue that when fund managers want to change their exposure to the market, they often to do so by titling towards large/small stocks or growth/value stocks. As a result, when these factor effects are considered in timing models, any misidentified market timing will be removed. Indeed, Chen *et al* (2013) show that growth-oriented funds in their sample invest over 90% of their assets under management in the stock market and these mutual funds only adjust overall market exposure slightly.

To address whether fund managers tend to adjust portfolio exposure to factors, Daniel *et al* (1997) propose an alternative holdings-based timing measure, specifically to explore whether changes in portfolio weights of size, book-to-market and momentum factors can forecast future returns. By examining quarterly holdings of a sample of over 2500 mutual funds, the authors find that there is no significant characteristic-timing performance across all categories of funds in their sample, and the characteristic-timing performance is never significantly positive for any subgroup of funds in any sample period. This suggests that on average fund managers are not able to successfully forecast the time-varying expected returns of style factors.

Chen *et al* (2013) argue that one reason previous studies fail to detect timing ability is that researchers consider market timing ability or characteristic-timing ability in aggregate. Fund managers might possess timing ability in subsets of the market. These authors focus on exploring the style-timing skill “star” fund managers might possess and to what extent style-timing abilities can explain the superior performance of star fund managers. Using a return-based approach, Chen *et al* (2013) show that “star” fund managers possess “growth” timing ability but not market timing ability. The “star” fund managers in their sample appear to be able to generate abnormal performance from switching stocks in their portfolios along the value/growth continuum. Chen *et al* (2013) further argue that “growth” timing performance explains at least 45% of the abnormal returns they find. Consistent with Elton et al

(2012)'s argument, Chen *et al* (2013) demonstrate that growth timing strategies can be easily misidentified as market timing skill.

More importantly, Chen *et al* (2013) advocate the characteristic-timing measure of Daniel *et al* (1997) to explore differential fund manager trading skills. These authors argue that the characteristic-timing method considers changes in fund holdings at the individual stock level, and thus, it can be used to explore for differential fund manager trading skills. By focusing on "star" growth-oriented fund managers who exhibit superior past performance, Chen *et al* (2013) break down the characteristic-aggregate timing performance into the characteristic-timing returns for buying and selling, and show that these "star" fund managers possess positive buying skill and negative sell skill. The authors point out that the lack of evidence of mutual fund characteristic timing ability might be due to the fact that Daniel *et al* (1997) and other studies on mutual fund timing ability identify and measure timing performance only in aggregate terms. However, as discussed earlier, their study is subject to some criticisms. Chen *et al* (2013) use at least 36 months of past monthly fund return data to identify superior performing funds. This sample selection procedure not only excludes young mutual funds that do not have a sufficiently long return history, but also induces survivorship bias. Their analysis might also overestimate the trading skills along both buying and selling dimensions because their small group of growth-oriented mutual fund managers are more likely to possess genuine skill, rather than luck (Kosowski *et al*, 2006). As such, it is unclear whether their results are generalizable to other mutual funds, particularly those with average and even below-average historical performance.

Indeed, Norris (2002) argues that a decision to sell stocks involves changing investors' mind about the prospects of the investments, which can be particularly difficult in the investment world, where investors are swamped with incomplete information. Thus, behavioural and emotional bias can play an important role in forming sell decisions. In fact, the behavioural finance literature has long recognised that selling decisions are particularly susceptible to behavioural biases. For instance, several studies of selling behavior in natural and experimental markets provide evidence that investors are more reluctant to realize losses than gains (Odean, 1998; Weber and Camerer, 1998). Shefrin and Statman (1985) label this phenomenon the "disposition effect". Working with a discount brokerage database, Odean (1998) finds that the retail investors in his sample tend to sell winning stocks relative to their purchases prices, rather than losing stocks. Evidence of the disposition effect can also be found in other markets such as the housing market (Genesove and Mayer, 2001). Genesove and Mayer (2001) show that house sellers tend to set an asking price that exceeds the asking price of other sellers with comparable houses when the expected selling price is below their original purchase price. Odean (1998) and others argue that the disposition effect cannot be easily explained within the rational trading framework. First, investors might be motivated by tax consideration to sell losers, not winners. Second, such tendency to sell winners is not likely due to rational information and beliefs updates because Odean (1998) find that the stocks that investors sell outperform the stocks they choose to hold on to.

There are a number of behavioral explanations from the literature. First, investors may have an irrational belief in mean-reversion (Barberis and Thaler, 2003). Second, mental accounting may help explain the disposition effect. In particular, investors tend to separate mental accounts for gains and losses in making decisions (Thaler, 1985). Third, the disposition effect can be understood with a prospect theory framework. Kahneman and Tversky (1979) argue that people are risk averse towards gains but risk seeking toward losses and thus their expected utility function is concave (convex) in the region of gains (losses). Coval and Shumway (2005) show that professional traders who have profits (losses) by the middle of the trading day will take less (more) risk during the remaining of the day. Fourth, Hirshleifer (2001) argues that self-deception theory reinforces this argument because a loss is an indicator of low decision ability. People tend to avoid accepting such a signal.

On the other hand, behavioural biases can lead to the opposite selling phenomenon that investors tend to hold winners too long before selling them. One of the behavioural explanations is the "endowment effect", a tendency for people to hold on what they already possess rather than to exchange for a better alternative (Knez *et al*, 1985; Kahneman *et al*, 1991).

Despite these findings in earlier studies, little empirical work has been done to evaluate professional investors' buying and selling abilities separately. One exception is Faugere *et al* (2004) who argue that the finance literature has concentrated on the buy decision, but has been largely silent on the sell decision. The authors point out that it is because researchers have no reliable sell discipline criteria to assess the performance of sell decisions. By using six sell criteria obtained from the Plan Sponsor Network (PSN) database, Faugere *et al* (2004) examine the impact of sell discipline on monthly fund performance and show that the effectiveness of selling discipline is determined by overall market conditions. Overall, they demonstrate that the choice of selling discipline has a significant impact on portfolio performance.

Summarizing, most studies in the literature have concentrated on the stock-picking ability of mutual fund managers but overlooked the additional performance that might be generated by timing ability. A number of the early studies that investigate whether mutual fund managers have timing ability are criticized for making strong assumption that fund managers implement timing strategies in a specific way, even though they might implement timing strategies in a more complex manner. The return-based measures typically employed in the literature are also subject to the "artificial timing" effects. Such issues can lead to the incorrect inference about the timing abilities that mutual fund managers really possess. On the other hand, holdings-based studies have found mixed results regarding fund manager timing ability. Whether fund managers or subsets of fund managers have timing ability in aggregate or differential trading skills is still open to further research.

2.3 Methodology

This section describes the main measures of fund manager skills, including the "characteristic-selectivity" measure (CS) for stock-picking ability and the "characteristic timing" measure (CT) for timing ability. To calculate these measures, I summarise the procedure to construct benchmark portfolios based on Daniel *et al* (1997)'s approach. I also describe the measures of style drift proposed by Wermers (2012) as a proxy for fund manager conviction.

2.3.1 Measuring Fund Performance

This chapter first calculates the buy-and-hold hypothetical monthly returns that would be generated by purchasing the number of shares of each stock held by mutual fund (common stocks with share code 10 and 11 in the CRSP universe) on the first day of each holding report until the first day of the following holding report.[4] The hypothetical gross monthly return is defined as:

[4] This chapter retrieves all holding reports in the CRSP Mutual Fund Database, accounting for the irregularity of mutual fund holding reports and update holding weights by using the most recent report available.

$$RET_t = \sum_{j=1}^{N} \widetilde{\omega}_{j,t-1} \tilde{R}_{j,t} \quad (1)$$

where $\widetilde{\omega}_{j,t-1}$ is the portfolio weight on stock *j* at the end of month *t-1*, and $\tilde{R}_{j,t-1}$ is the month *t* return of individual stock *j* held by fund at the end of month *t-1*. Following Daniel *et al* (1997), the most recent portfolio holdings available for a fund from the CRSP mutual fund holding database are used to estimate the portfolio weights on stocks.[5]

Following Daniel *et al* (1997), hypothetical monthly returns are reported as the gross returns of mutual funds, and the overall fund performance is decomposed into CS, CT, and AS based on a stock characteristic-based approach. This characteristic-based approach requires the construction of passive benchmark portfolios that can be matched to individual stocks in the mutual fund portfolios with the dimensions of market value of equity (size), book-to-market ratio (btm), and momentum effect (mom). This chapter constructs passive benchmark portfolios according to the procedure detailed in Daniel *et al* (1997). Briefly, at the end of June each year, the common stocks listed on the NYSE, AMEX, and NASDAQ are categorized into three quintile groups based on the individual stock's size, book to market ratio and prior year return and $5 \times 5 \times 5$ sorted characteristic-based portfolios are formed. The monthly returns of these benchmark portfolios are calculated as the monthly value weighted returns of the stocks in the 125 portfolios. The detailed procedure is described in Daniel *et al* (1997).

The first component of gross return is the "characteristic-selectivity" attribute (CS). The CS measure, is the excess return of a particular stock in portfolio, which is

[5] These most recent holdings are usually the holdings at the end of the most recent calendar quarter.

calculated by subtracting the return of the matched passive benchmark portfolio from the return of individual stocks. The value weighed excess return of all stocks in the portfolio gives us the CS measure and a significantly positive time series average of CS measure indicates that this mutual fund manager has stock-picking ability that outperforms the passive benchmark portfolios. The CS measure is defined formally as:

$$CS_t = \sum_{j=1}^{N} \widetilde{\omega}_{j,t-1}(\tilde{R}_{j,t} - \tilde{R}_t^{b_{j,t-1}}) \quad (2)$$

where $\widetilde{\omega}_{j,t-1}$ is the portfolio weight on stock j at the end of month *t-1*, $\tilde{R}_{j,t-1}$ is the month t return of individual stock *j* held by fund at the end of month *t-1*, and $\tilde{R}_t^{b_{j,t-1}}$ is the month t return of the characteristic-based passive benchmark portfolio that is matched to individual stock *j* according its size, book to market and momentum during the month *t-1*.

The second component is the "characteristic timing attribute" (CT) of the gross return. The CT measure captures the performance generated from the timing abilities of mutual fund managers. Daniel *et al* (1997) argue that fund managers can produce performance by changing the portfolio weights on the stock characteristics along the dimensions of size, book to market, and momentum if there were trading strategies based on these characteristics which have time-varying expected returns. The CT performance therefore tests if mutual fund managers have the timing ability to correctly allocate and adjust portfolio weights to the different risk factors in aggregate over time and it measures the performance that mutual fund managers can generate from timing these stock characteristics. The month t of the CT measure is defined as:

$$CT_t = \sum_{j=1}^{N} (\widetilde{\omega}_{j,t-1} \tilde{R}_t^{b_{j,t-1}} - \widetilde{\omega}_{j,t-13} \tilde{R}_t^{b_{j,t-13}}) \qquad (3)$$

where $\widetilde{\omega}_{j,t-1}$ is the portfolio weight on stock j at the end of month *t-1*, $\widetilde{\omega}_{j,t-13}$ is the portfolio weight on stock j at the end of month *t-13*, $\tilde{R}_t^{b_{j,t-1}}$ is the month t return of the characteristic-based passive benchmark portfolio that is matched to individual stock *j* according to its size, book to market and momentum during month *t-1*, $\tilde{R}_t^{b_{j,t-13}}$ is the month *t* return of the characteristic-based benchmark portfolio that is matched to stock *j* during month *t-13*.

To illustrate the rationale behind the CT measure, suppose that a fund increases its weights in high book-to-market stocks at the beginning of the month in which the book-to-market effect was unusually strong during that month, the this fund would have positive CT performance for that month. A significant and positive time series average of the CT measure indicates a superior characteristics-timing ability.

The third component is the returns generated due to the tendency of mutual funds to hold stocks with certain characteristics. The “average style attribute” (AS) measure is calculated as:

$$AS_t = \sum_{\boldsymbol{j=1}}^{\boldsymbol{N}} \widetilde{\omega}_{j,t-13} \tilde{R}_t^{b_{j,t-13}} \qquad (4)$$

where $\widetilde{\omega}_{j,t-13}$ is the portfolio weight on stock j at the end of month *t-13*, and $\tilde{R}_t^{b_{j,t-13}}$ is the month *t* return of the characteristic-based benchmark portfolio that is matched to stock *j* during month *t-13*.

2.3.2 Measuring Fund Manager Conviction

The nature of open-end mutual funds might force fund managers to make investment decisions for reasons other than valuation beliefs. To capture the investment skills which fund managers really possess, this chapter attempts to identify ex ante which investment decisions are more likely to represent fund managers' conviction (or false beliefs) and to evaluate the performance of those decisions. In order to investigate the relationship between the strength of fund manager conviction and characteristic-timing performance, this chapter employs the non-parametric measure of Wermers (2012) as the main proxy for fund manager conviction.

Following Wermers (2012), the total style drift of a managed portfolio in style dimension *l* (where *l* = size, book-to-market, or momentum) at portfolio reporting date *q* is measured as:

$$TSD_q^l = \sum_{j=1}^{N} \left(\widetilde{w}_{j,q} \tilde{C}_{j,q}^l - \widetilde{w}_{j,q-1} \tilde{C}_{j,q-1}^l \right) \quad (5)$$

where $\widetilde{\omega}_{j,q}$ is the portfolio weight on stock *j* at the end of quarter q and $\widetilde{\omega}_{j,q-1}$ is the portfolio weight on stock *j* at the end of quarter *q-1*, while $\tilde{C}_{j,q}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter *q* and $\tilde{C}_{j,q-1}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter *q-1*.

The total style drift for each fund each quarter can be further decomposed into an active style drift that results from active changes in the portfolio through active trades of stocks and a passive style drift that results from passively holding stocks with changing holding weights and stock characteristics.

$$\mathrm{TSD}_q^l = PSD_q^l + ASD_q^l \quad (6)$$

Where PSD_q^l measures the change in style dimension *l* assuming that the manager passively hold the portfolio during quarter *q-1* to quarter *q* while ASD_q^l measures the change in style dimension *l* through buys and sells of stocks during quarter *q-1* to quarter *q*.

PSD_q^l or passive style drift in dimension *l* during quarter *q-1* to quarter *q* is measured as:

$$PSD_q^l = \sum_{j=1}^{N} \left(\widetilde{w}'_{j,q} \tilde{C}_{j,q}^l - \widetilde{w}'_{j,q-1} \tilde{C}_{j,q-1}^l \right) \tag{7}$$

where $\widetilde{w}'_{j,q}$ denotes the portfolio weight of stock *j* at the end of quarter *q* when a manager buys and holds the entire portfolio during quarter *q-1* to quarter *q* while $\tilde{C}_{j,q}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter *q* and $\tilde{C}_{j,q-1}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter *q-1*.

The remainder of total style drift is captured by ASD_q^l or the active style drift:

$$ASD_q^l = \sum_{j=1}^{N} \left(\widetilde{w}_{j,q} \tilde{C}_{j,q}^l - \widetilde{w}'_{j,q} \tilde{C}_{j,q}^l \right) \tag{8}$$

where $\widetilde{\omega}_{j,q}$ is the portfolio weight on stock *j* at the end of quarter *q* while $\widetilde{w}'_{j,q}$ denotes the portfolio weight of stock *j* of quarter *q* when a manager buys and holds the entire portfolio during quarter *q-1* to quarter *q* and $\tilde{C}_{j,q}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter *q*.

Total, passive and active style drifts are then aggregated across all three dimensions of size, book-to-market and momentum effects for a fund during the period between quarter *q-1* to quarter *q* as:

$$TSD_q = \left|TSD_q^{size}\right| + \left|TSD_q^{btm}\right| + \left|TSD_q^{mom}\right| \tag{9}$$

$$PSD_q = \left|PSD_q^{size}\right| + \left|PSD_q^{btm}\right| + \left|PSD_q^{mom}\right| \tag{10}$$

$$ASD_q = \left|ASD_q^{size}\right| + \left|ASD_q^{btm}\right| + \left|ASD_q^{mom}\right| \tag{11}$$

A non-zero value of active style drift would primarily occur due to active changes in portfolio weights of stocks through buys and sells. For example, in the style dimension of book-to-market, a fund manager who believes that the book-to-market effect would be unusually strong in the following month could allocate more portfolio weight to high book-to-market stocks through buying high book-to-market stocks or selling low book-to-market ones.

2.4 Data and Sample

In this section, I begin by describing my data on mutual funds holdings, their characteristics and their returns. I also describe data on individual stocks, including price and accounting data. Following this, I present the screening procedure I use to select U.S. domestic actively managed equity mutual funds.

2.4.1 Mutual Fund Holdings Data

My portfolio holdings data from September 2003 to December 2013 for U.S. actively managed domestic equity funds is created by merging the CRSP Survivorship Bias Free Mutual Fund Database with the CRSP stock price database. 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 and management fee, turnover ratio, investment objectives, first offer date and other fund characteristics for each share class of every U.S. open-end mutual fund. The CRSP Mutual Fund Database also provides information on reported portfolio holdings of mutual funds since September 2003, including the identification of portfolios (crsp_portno), holdings report date (report_dt), the effectiveness date of the report (eff_dt), stock identification number (permno), number of shares held in the portfolio (nbr_shares), and market value of the stocks held (market_val). The holdings data in the CRSP Mutual Fund Database is collected both from reports filed with the SEC and from voluntary reports generated by the mutual funds themselves. The CRSP mutual fund characteristic/returns dataset for each share class of every common mutual fund is linked to the holdings dataset of mutual fund portfolios by using the map (portnomap) provided by the CRSP mutual fund database. The map dataset contains information on the identification of individual share classes (crsp_fundno) and their common funds (crsp_portno) over time, as well as other share class characteristics including delist date, delist type, and the identification of the acquirer share classes and the latest available date for monthly net assets value for target share classes.

2.4.2 Price and Accounting Data

Data on stock identification, stock return, delist return, share price, trading volume, cumulative price adjustment factors, cumulative shares adjustment factors, and shares outstanding as well as other stock characteristics are obtained from the CRSP stock price database. This CRSP price dataset[6] is then merged with the CRSP Mutual Fund database by matching stock identification (permno) and holding report date

[6] 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.

(report_dt). This chapter estimates mutual fund trades by tracking changes in holdings from report to report. In order to follow changes in stock holdings correctly, the number of shares held in portfolios is adjusted by the CRSP cumulative shares adjustment factors.[7] Data used to estimate book value of equity for stocks in the way by 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.

2.4.3 Sample Selection

This chapter follows and modifies the procedure of Kacperczyk *et al* (2008) to select U.S. domestic equity mutual funds.[8] This chapter starts with all mutual fund samples in the CRSP Mutual Fund Database universe. Since the focus of the analysis is on actively managed U.S. domestic equity mutual funds for which holdings data are most complete and reliable, this chapter eliminates balanced, bond, money market, international, sector, index, ETF, exchange target, and target date funds as well as those funds not invested primarily in equity securities. This screening procedure generates a sample of 109054 fund-report observations with a total of 3384 unique U.S. domestic equity mutual fund samples from September 2004 to December 2013. Appendix A at the end of the thesis provides the detailed screening procedure.

Panel A of Table 2.1 reports the number of domestic equity mutual funds in each year along with summary statistics of some fund characteristics. There is a significant rising

[7] The CRSP Mutual Fund Holdings Database changed its data source since October 2010. Before October 2010, the reported number of shares in portfolio for stock distribution events such as splits is already adjusted and therefore we need to re-adjust it back before calculating changes in shares and market value of holdings.
[8] This report also follows a note writen by Glushkov and Moussawi (2010) from WRDS on selecting actively managed U.S. domestic equity mutual funds.

trend in the number of funds in our sample, while the average total net assets under management (TNA) peaked at $1512 million in the year 2006 and dropped dramatically to $ 821 million by almost 50% during the financial crisis. The median of total net assets followed the same pattern. Overall there is an increasing trend in both mean and median of fund size but a decreasing trend in expense ratio. On average, mutual fund managers appear to hold a similar number of stocks in their portfolio but seem to buy and sell fewer stocks per month over time. Turnover ratio peaked in 2009, indicating that mutual fund managers traded more frequently along the financial crisis. Panel B reports the summary statistics of funds with different investment objectives. In particular, Income funds tend to trade much less frequently than other investment objective groups and Micro-Cap funds charge investors the highest expense ratio.

Table 2.2 examines the overall portfolio styles for mutual funds with different self-declared investment objectives. In order to characterize the investment style reflected in the portfolio holdings of different mutual funds, this chapter follows Daniel *et al* (1997) and Wermers (2012) to construct a database that maps each stock-year to the quintile numbers (one through five) in each style dimension of the size, the ratio of the book value of equity to the market value of equity (book-to-market), and the one-year lagged return of the stock (momentum). Quintile number 1 denotes small market capitalisation, low book to market or poor prior year return. Quintile number 5 denotes large market capitalisation, high book to market or good prior year return. These quintile numbers are then assigned to each corresponding stock held by fund portfolios during a given quarter and portfolio weighted quintile numbers for each mutual fund are calculated for that quarter. To illustrate the procedure, suppose a fund invests 50% in small market capitalisation, quintile 1; low book to market, quintile 1 and poor prior year return, quintile 1. Simultaneously, this fund invests the other 50% in large market capitalisation, quintile 5; high book to market, quintile 5 and good prior year return, quintile 5. The average style of the fund will thus equal 3 for each of market capitalisation, book to market and prior year return during that quarter. These style numbers for each mutual fund are averaged across all funds in the same market segment during the quarter. Finally, the time series average of style numbers along the three dimensions are calculated over the sample period from 2004 to 2013.

As we can be seen from Table 2.2, the full sample of mutual funds has an above median size (3.78) and momentum (3.10) and lower book to market (2.88). On average, the results for different investment style groups are fairly consistent with their self-declared investment objectives. In particular, the micro-cap funds invest heavily in small size firms (1.47), growth firms (2.58) and relatively higher momentum stocks (3.10). Income funds invest mostly in firms with large size (4.72), higher book to market (3.17) and relatively lower momentum factor (2.76). Mutual fund managers may possess the ability to time these characteristics and adjust the portfolio exposure to these style factors over time in an attempt to exploit time-vary characteristic returns. This will cause shift in the portfolio styles away from their target styles or the self-reported investment objectives. The following sections examine whether mutual fund managers have characteristic-timing ability and whether changes in portfolio styles result in superior characteristic-timing performance.

2.5 Empirical Results

2.5.1 Aggregate Characteristic-Timing Performance

This chapter first reports an overview of fund performance of my sample of U.S. domestic equity mutual funds over the 10-year period from 2004 to 2013. Column (2) to column (4) of Table 2.3 provide a year-by-year comparison of the average gross returns of all mutual funds in the sample with the average buy-and-hold monthly return for the CRSP value weighted and equally weighted NYSE/AMEX/NASDAQ portfolios without distribution. Comparisons indicate that at first glance, mutual fund managers appear to outperform the two passive portfolios of the CRSP stock universe. For instance, the average gross return of mutual funds before any expense and commissions is 11.29%, while the value-weighted (equally-weighted) hypothetical portfolio of all stocks in CRSP universe is only 7.39% (9.23%) for the period from 2004 to 2013 in our study. However, this outperformance does not hold when we control for the cross-sectional differences in stock returns, due to stock characteristics of size, book-to-market and momentum effects by using the Daniel *et al* (1997) performance measures.

In particular, the last three columns on the right of Table 2.3 report the three different performance attributes proposed by Daniel *et al* (1997). "CS Performance" captures the stock picking ability of mutual fund managers by mitigating performance generated due to cross-sectional differences in stocks returns attributable to the size, book-to-market, and momentum anomalies. Results in Table 2.3 indicate that on average mutual fund managers have a negative but insignificant stock selectivity ability over the sample period from 2004 to 2013, with statistically insignificant -2 basis point per year before expense. Yearly results also show that, on average, stocks held in mutual fund portfolios could not outperform passive characteristic-benchmark portfolios. The CS measure is positive in eight years, but only significantly at the 10% significance level in 2005 and 2013, with an average of 1.86% per year and 1.02%, respectively, and negative in two years, but neither of them is statistically significant. Sub-period results show that CS performance is positive, with an average of 0.78% and 0.43% per year, during the periods before and after the recession, respectively, while CS performance is negative, with an average of -2.80% per year during the recession. However, none of these values is statistically significant, though the t-statistic for CS performance before the recession is 1.51. Overall, these results are consistent with the consensus view in the literature that on average mutual fund managers are not able to outperform their passive benchmarks. Recent empirical studies in the U.S. market suggest little or no evidence of superior mutual fund performance, but show strong evidence of persistent poor performance.[9]

The CT measure is designed to detect any additional performance from successfully timing stock characteristics. Overall, we can see that on average, CT performance is -37 basis points per year but is statistically insignificant with a t-statistic -1.57 from 2004 to 2013, consistent with the results of Daniel *et al* (1997). In other words, mutual fund managers do not exhibit any characteristic timing skills, but instead, there is weak evidence to show that they actually have negative timing performance at a marginally significant level. Separate yearly results show that CT measure is negative but insignificant in eight years except for year 2008. Sub-period results confirm that there is no evidence of timing skills: average CT performance is -42 basis points per year but is insignificant with a t-statistic of -1.61 before the recession, while average CT performance is -46 basis points per year, statistically significant at 10% level, with t-statistic of -1.82, after the recession. Fund managers tend to have economically significant and negative characteristic-timing performance during expansion period. Interestingly, during the recession from December 2007 to June 2009, CT performance is only -3 basis points per year, and it is not statistically different from zero. The difference in characteristic-timing performance between recession and

[9] See e.g., Blake and Timmermann, 1998; Blake et al 1999; Thomas and Tonks, 2001, Cuthbertson *et al*, 2008

expansion market conditions is economically meaningful and it is mainly driven by the poor performance during the expansion periods. In other words, fund managers appear to have some timing abilities, at least showing non-negative characteristic-timing performance, during the recession. This finding is consistent with Kacperczyk *et al* (2014) who find that fund managers have time-varying skills. Fund managers tend to perform stock picking well in expansions and time the market well in recessions.

Table 2.4 reports the CS, CT, and AS performance attribution components for funds in different investment categories. Panel A shows that in the analysis of the entire sample period on average, CS performance for all mutual fund investment categories is never statistically significant, indicating that none of the mutual fund categories on average is able to outperform their passive benchmark portfolios. In terms of characteristic-timing ability, only Micro-Cap mutual funds exhibit negative and statistically significant CT performance, with an average -79 basis points per year, while the other investment objectives have negative but insignificant CT performance.

Sub-period analysis provides strong evidence that no investment category of fund managers possesses positive characteristic-timing skills while fund managers in some investment categories exhibit positive stock-picking performance in expansions but significantly negative performance in recessions. Panel B presents the performance results during the first sub-sample period from September 2004 to December 2007. Micro-Cap funds exhibit significantly positive CS performance of 2.83% per year but significantly negative CT performance of -0.96% per year and Mid-Cap funds also exhibit significantly positive CS performance of 1.56% per year but significantly negative CT performance of -0.55% per year. All other investment categories do not show any significant CS and CT performance. Panel C reports performance during the recession period. None of the CT performance measure for any investment category is significantly different from zero. CS performance for all investment categories is all negative and only Micro-Cap funds exhibits unsuccessful stock picking performance with significant CS performance of -9.47% per year during the recession period. Panel D covers the period after the recession and results show that during this period, CT performance for Growth and Income funds, Income funds, and Micro-Cap funds are all significantly negative but CS performance for Micro-Cap funds is 3.63% per year, and is economically and statistically significant.

To summarize, we find that on average, mutual fund managers exhibit no superior investment performance. In particular, mutual fund managers have negative but insignificant stock selection ability over our sample period, indicating that fund managers are not able to pick stocks that deliver risk-adjusted abnormal performance. More interestingly, there is some evidence to show that fund managers appear to have, if any, negative characteristic-timing performance. In other words, fund managers tend to change the weights on the characteristics of the stocks held in the portfolios along the dimensions of size, book to market, and momentum in the wrong way, or at least they are not able to exploit the time-varying expected returns of these stock characteristics.

2.5.2 Buying and Selling Characteristic-Timing Abilities

Although a large number of studies in the literature find that mutual fund managers do not possess timing ability, there is no convincing evidence that directly explains why mutual fund managers underperform in the domain. Chen *et al* (2013) point out that the traditional CT measure, which is simply calculated by aggregating the characteristic timing performance of all holdings, would mask the distinct trading skills where the CT performance for buying and selling are calculated separately.

To explore distinct trading abilities, this chapter follows Chen *et al* (2013) to decompose aggregate CT performance into different trading components. Specifically, for each fund, I measure the changes in number of shares held in each stock from the end of quarter *t-1* to the end of quarter *t* for each quarter in the sample period. Increases in the number of shares are treated as buys and aggregated to form the buy portfolio and decreases are aggregated to form the sell portfolio, for each fund each quarter. Additionally, I aggregate stocks with no changes in number of shares between two quarters into the passive holding portfolio. This chapter then calculates the characteristic-timing performance for each trading portfolio. If a fund's purchases of stocks are associated with subsequent performance above prior average returns from stock characteristics, the characteristic-timing performance for the buy portfolio will be positive; if sales of stocks are associated with subsequent returns higher than prior average returns from stock characteristics, the characteristic-timing performance for the sell portfolio will also be positive. Similarly, if passive holdings are effective in terms of subsequent performance, the characteristic-timing performance for passive holdings will equally be positive. If a fund exhibits positive time series average characteristic-timing performance along buying (selling) dimension, this indicates that this fund manager possesses superior buying (selling) skill.

Panel A in Table 2.5 reports the CT performance for buying, selling and passive holdings for equity mutual funds during the whole sample period from September 2004 to December 2013. The second column reveals that whereas no overall characteristic-timing ability measured by aggregate characteristic-timing performance is found, this masks different skills along buying and selling dimensions. In general, mutual fund managers (All Funds) appear to exhibit significant timing ability when purchasing stocks. For example, mutual fund managers earn an average return of

1.42% per year (t-statistic=1.65) greater than the average across the three characteristic styles from their purchases, indicating that mutual fund managers possess skills in this domain. When breaking down mutual funds by their investment objectives, I find some evidence to show that growth oriented mutual funds (Growth and Mid-Cap funds) possess significant timing ability for buying stocks, while income oriented mutual funds (Growth & Income and Income funds) exhibit no statistically significant characteristic-timing performance when purchasing stocks. The difference of buying performance between growth and income funds is economically significant.

My results show that none of the investment categories of mutual funds earn significant characteristic-timing performance from holding the same stocks. This is consistent with the literature, suggesting that passive holdings represent fund managers' past investment beliefs and are not useful measures for detecting investment ability (e.g., Chen *et al*, 2000). My findings therefore contribute to the literature by showing a similar result in terms of characteristic-timing ability.

More interestingly, mutual fund managers exhibit poor characteristic-timing abilities when disposing of stocks in their portfolios. In general, the stocks mutual fund managers sell are associated with subsequent negative characteristic-timing returns of -1.78% per year (t-statistic=-1.86). None of the fund investment categories shows positive characteristic-timing performance for selling. These results indicate that on average, mutual fund managers are not able to generate characteristic-timing performance when selling their stocks but instead destroy the characteristic-timing performance generated from their buying activities.

To summarize, our results show that fund managers appear to possess significant timing ability over stock characteristics when purchasing stocks. In particular, growth oriented funds have greater stock buying skills than other income oriented funds. We also reveal that mutual fund managers seem to systematically fail to time the stock characteristic styles when selling stocks. None of the investment categories exhibit significant and positive characteristic-timing skills for selling. Also, there is no substantial performance variation among different investment objectives. To check the robustness of our results, we break our sample in to three different sub-periods, based on recessionary environment defined by NBER. Results from the sub-period analysis in the remaining of Table 2.5 are broadly similar with what we find in our full sample (Panel A). Overall, these findings are consistent with the fundamental asymmetry between buy and sell decisions in terms of trading disciplines found in the investment community. This chapter also offers empirical support to the theoretical predictions from the behavioural finance literature that sell decisions are susceptible to behavioural biases and heuristics that might affect investment performance.

2.5.3 Characteristic-timing Performance Persistence

To test for persistence of characteristic-timing performance, this chapter first sorts mutual funds into five performance quintiles each quarter based on aggregate, buying and selling CT measures respectively. We report the average characteristic-timing performance of each of the performance quintile portfolios during the formation quarter and track the performance over the subsequent four quarters. Panel A in Table 2.6 summarises the persistence results for aggregate performance while Panel B and Panel C present persistence results for trading activities.

There is weak evidence in Panel A to show that the difference in aggregate performance between past winners and losers continues to remain positive in the following four quarters after portfolio formation, suggesting that aggregate characteristic-timing performance is persistent. Surprisingly, a closer look reveals that such persistence of aggregate performance is mainly driven by the persistence of characteristic-timing performance in the negative domain. In particular, losers in performance quintile 1 who exhibit the worst characteristic-timing performance (-7.64% per year) in the formation quarter continue to have negative quarterly characteristic-timing performance of -0.87%, -0.46%, -0.87% and -0.75% per year in the following four quarters, while the future performance of past winners (7.26% per year) turn out to be negative immediately after the formation quarter. These results are consistent with recent studies such as Teo and Woo (2001) and Cuthbertson *et al* (2008) who observe strong persistence among poorly performing funds.

Panel B shows that the characteristic-timing performance when buying stocks is persistent. In particular, on average mutual funds in the performance quintile 1 that have the worst CT_{buy} performance in the formation quarter have positive CT_{buy} performance of 1.00%, 1.53%, 1.36%, and 1.41% per year in the subsequent four quarters. On the other hand, mutual funds that are particularly successful in buying stocks continue to have positive and statistically significant CT_{buy} performance of 2.39%, 1.85%, 1.94%, and 1.67% per year in the following four quarters. The performance difference between past winners and losers remain positive over four quarters and the outperformance of past winning funds is a statistically and economically significant average of 1.38% per year for at least the following quarter Q+1. These results suggest that a small number of fund managers have "hot hands" to buys stocks: fund managers who have the best past buying performance continue outperform those who display the worst buying ability in near term.

Similarly, results in Panel C report that mutual fund managers seem to have persistently bad characteristic-timing ability for selling. Mutual funds with the lowest

CT_{sell} performance in the quintile formation quarter display negative performance of -2.83%, -2.28%, -2.56%, and -2.14% per year while mutual funds with highest past CT_{sell} performance exhibit negative performance of -1.44%, -1.90%, -1.55%, and -1.74% per year during the following four quarters. Past losers continue to underperform past winners by a statistically significant amount of 1.43% in quarter Q+1. This underperformance is also economically meaningful. These results suggest that there is a small number of mutual fund managers who exhibit "icy hands" in selling stocks in short term.

Overall, this chapter documents the strong persistence of aggregate characteristic-timing performance in the negative domain over the following four quarters, indicating that mutual fund managers do not possess characteristic-timing ability in aggregate but instead a subset of fund managers tend to have poor timing ability that persistently destroys portfolio value. I also find strong evidence to show that characteristic-timing performance along both buying and selling dimensions is persistent in near term. In particular, mutual fund managers who exhibit superior characteristic-timing performance when buying stocks in the past tend to continue performing buying tasks well, while those who were the worst performers in selling stocks tend to underperform in the sell domain in short term. Extreme positive (negative) performance for selling (buying) is due to good (bad) luck. These results reinforce our main hypothesis that mutual fund managers have distinct trading skills.

2.5.4 Fund Manager Conviction and Characteristic-Timing Performance

The final tests examine the relationship between fund manager conviction and subsequent characteristic-timing performance. If mutual fund managers are skilled, strong fund manager conviction, as reflected in large style changes in allocation toward equity style factors in the their portfolio, should be associated with superior subsequent characteristic-timing performance. However, if large style drifts were made due to other reasons such as overconfidence or gambling behaviour, we might find a non-linear or negative relationship between the strength of fund manager conviction and subsequent characteristic-timing returns. To capture the effect of fund manager conviction on subsequent performance, I employ active style drift as our main proxy for fund manager conviction, which allows us to precisely measure change in portfolio style through active trading. At the end of each quarter, mutual funds in our sample are ranked and are divided into quintile groups based on the level of active style drifts. I evaluate and analyse subsequent fund performance for each of the portfolios conditioning on the strength of fund manager conviction.

Table 2.7 shows that large active style drift is not associated with superior performance from stock picking (CS performance). When funds engage into aggressive style drift (Top 20%), on average they earn an insignificant 0.07% characteristic-timing return per year, while those who have little style drift to their portfolio (Bottom 20%) have an insignificantly negative -0.07% return per year. There is no significant difference in the CS performance between these two quintiles.

My results concerning characteristic-timing ability show that no quintile groups of active style drift exhibits positive characteristic-timing returns (CT performance). This is consistent with my main findings: mutual fund managers in general lack the timing ability to correctly allocate portfolio weights across the three style factors. More importantly, aggregate characteristic-timing performance is not increasingly related to the strength of fund manager conviction. Instead, Table 2.7 shows that mutual funds in the top (bottom) quintile underperform those who experience moderate active style drift by -0.49% (-0.41%) with t-statistic of -1.67 (-1.95), which reveals a strong inverted-U relationship between fund manager conviction and subsequent characteristic-timing performance. In particular, most aggressive active style drift (Top 20%) is associated with statistically and economically significant but negative aggregate characteristic-timing returns of -0.66% per year (t-statistic=-2.31). In other words, strong fund manager conviction is associated with diminished subsequent characteristic-timing returns, suggesting that there might be more than valuation beliefs in shaping characteristic-timing decisions. On the other hand, the least active style drifts are also associated with significantly negative characteristic-timing performance of -0.57% per year (t-statistic=-1.80), which is consistent with the expectation that small active style drifts represent weak fund managers' beliefs about future performance.

By breaking down aggregate performance into buying and selling components, I find that large style bets are associated with insignificant characteristic-timing performance for buying but negative returns when selling stocks. In particular, although mutual fund managers who have the strongest conviction tend to exhibit a positive characteristic-timing return of 2.01% per year when buying stocks, this characteristic-timing performance is not statistically different from zero. Large standard errors indicate that there are significant cross-sectional variations of characteristic-timing returns for fund managers who choose to engage in large style drifts. However, on average these fund managers are also unable to outperform those who belong to the bottom quintile of active style drifts when adding stocks into their portfolios. On the other hand, sale of stocks in the top quintile of portfolios with the highest levels of active style drift actually generates a poor characteristic-timing return of -2.97% per year (t-statistic=-1.87) and these fund managers underperform those who exhibit the least style drift in terms of selling characteristic-timing performance, by a statistically and economically significant amount of -1.98% per year, suggesting a clear negative relationship between fund manager conviction and the characteristic-timing performance when selling stocks. It is also interesting to note that purchases of stocks, in portfolios with moderate style drift, are able to generate positive and significant characteristic-timing returns, enough to offset the damage caused by poor selling ability.

To conclude this section, these results reinforce the main hypothesis of this chapter that mutual fund managers are not able to generate performance form exploiting time-varying expected returns of the three factor styles, by showing that aggregate characteristic-timing performance is not increasing in strength of fund manager conviction measured by the level of active style drift. In contrast, a strong inverted-U relationship between fund manager conviction and subsequent characteristic-timing performance is found. Large active style drifts, that should contain stronger fund managers' beliefs on future performance, are associated with negative aggregate characteristic-timing performance. A closer look reveals that such underperformance is mainly driven by poor selling ability. These results suggest that there are more than valuation beliefs in shaping fund managers' characteristic-timing decisions, in particular sell decisions.

2.6 Conclusion

This chapter re-examines whether mutual fund managers, a representative group of professional investors, exhibit investment abilities, and in particular, whether they possess the skill to produce performance from adjusting portfolio exposure to the risk factors including the size, book-to-market and momentum effects. Consistent with Daniel *et al* (1997) and others, I find no evidence of significant aggregate characteristic-timing skill. Further results reveal a strong persistence of aggregate characteristic-timing performance in the negative domain, which again indicates that mutual fund managers do not possess characteristic-timing ability in aggregate but instead a subset of fund managers tend to have poor timing ability that persistently destroys overall portfolio value.

In an attempt to explain such underperformance from characteristic-timing decisions, this chapter disaggregates overall characteristic-timing performance into different trading components. Consistent with Chen *et al* (2013), my results show that in general mutual fund managers possess positive characteristic-timing ability when buying stocks but negative trading ability when selling stocks. Performance persistence tests confirm that these distinct trading "skills" are driven by systematic factors. Mutual fund managers who were successful in buying stocks tend to continue generating superior characteristic-timing performance when purchasing stocks, while those who were the worst sellers tend to remain underperformed when disposing of stocks in near term. In other words, there are a small number of mutual funds exhibiting "hot hands" ("icy hands") in buying (selling) stocks. Overall, I argue that, the lack of evidence on superior general performance masks differential trading "skills".

By segmenting portfolios on the basis of active style drift as a proxy for fund manager conviction, I find a clear inverted U-shaped relationship between the strength of fund manager conviction and subsequent characteristic-timing performance. In particular, strong conviction as reflected in aggressive active style drift is associated with poor subsequent characteristic-timing performance. A closer look reveals that the negative aggregate characteristic-timing performance is mainly driven by poor selling activities.

Table 2.1 Summary Statistics of Mutual Fund Samples

The table below reports the summary statistics of a total of 3384 unique U.S. domestic equity mutual fund samples from September 2004 to December 2013. 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 U.S. Database. CRSP investment objective variable (crsp_obj_cd) is used to filter U.S. 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. Total number of funds is the total number of unique mutual funds that exist during the sample periods. Avg number of stocks is the times series average of cross-sectional average of the number of unique stocks held by mutual funds during the sample periods. Avg number of buys and sells are the time series average of cross-sectional average of changes in shares of stocks held by mutual funds between holdings reports. Avg TNA is times series average of cross-sectional average of total net assets under management of mutual funds. Avg Flow is time series average of cross-sectional average of estimated percentage change in TNA adjusted for investment return and mutual fund mergers. Avg Turnover is time series average of cross-sectional average of mutual fund turnover ratio. Avg Exp is time series average of cross-sectional average expense ratio of mutual fund. 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.

	Total Number of Funds	**Avg Number of Stocks**	**Avg Number of Buys**	**Avg Number of Sells**	**Avg TNA (in $ Million)**	**Median TNA (in $ Million)**	**Avg Flow (%/Month)**	**Avg Turnover (%/Year)**	**Avg Exp Ratio (%/Year)**
Panel A: Summary statistics of all mutual fund samples over time									
2004	1360	126.94	53.59	45.01	$1,327.63	$178.00	7.24	89.54	1.34
2005	1459	120.09	47.73	45.53	$1,354.98	$197.80	5.56	86.17	1.29
2006	1479	112.61	43.43	41.69	$1,512.18	$224.40	3.95	86.13	1.28
2007	1638	114.71	41.90	41.88	$1,483.71	$202.20	2.63	91.09	1.25
2008	2046	115.75	39.24	41.19	$821.48	$124.40	0.31	88.76	1.19
2009	2022	122.04	41.56	42.21	$1,059.28	$162.75	1.89	100.46	1.20
2010	2727	109.65	34.06	36.67	$1,097.55	$210.40	3.05	90.41	1.18
2011	2612	103.05	30.49	30.80	$1,011.80	$201.85	1.57	83.66	1.16
2012	2577	117.82	30.74	34.32	$1,105.19	$218.70	1.19	79.77	1.12
2013	2454	120.80	32.59	34.14	$1,502.37	$321.85	7.29	72.94	1.10
Panel B: summary statistics of mutual fund with different investment objectives									
All	3384	115.90	38.15	37.87	$1,217.94	$205.20	7.25	87.19	1.22
Growth	1529	100.48	33.76	33.51	$1,933.87	$254.50	10.89	92.59	1.22
Growth&Income	576	103.45	33.22	35.74	$1,332.02	$181.00	4.68	71.76	1.11
Income	191	78.90	25.74	21.00	$1,508.81	$317.60	14.48	48.60	1.09
Micro-Cap	50	111.93	31.05	37.32	$187.91	$101.65	2.71	92.92	1.66
Small-Cap	679	170.93	55.23	53.59	$843.47	$233.75	1.55	89.91	1.29
Mid-Cap	470	113.35	37.99	37.66	$728.33	$201.60	5.99	97.00	1.24

Table 2.2 Stock Characteristic (Style) in Fund Portfolio

This table reports the average characteristic (or style) for funds in different investment objective groups. For each year, each of the stock held by each mutual fund are identified into three characteristics, namely market capitalization, book-to-market and prior year return. They are classified into 1 to 5 depending on the quintile benchmark portfolio. Size classified as 1 denotes small stock; book to market classified as 1 denotes stock with low book to market; momentum classified as 1 denotes stock with low prior year return. For each quarter, the portfolio weighted average benchmark portfolio number is computed for each mutual fund. These fund average benchmark portfolio numbers are averaged across all funds for each year and each category.

	Average Size Quintile	**Average Book-to-Market Quintile**	**Average Momentum Quintile**
All Funds	3.78	2.88	3.10
Micro Cap	1.47	2.58	3.41
Small Cap	2.53	2.74	3.27
Mid Cap	3.95	2.69	3.14
Growth	4.50	2.84	3.12
Growth and Income	4.64	3.09	2.97
Income	4.72	3.17	2.76

Table 2.3 Mutual Fund Performance in Aggregate, All Samples

This table below reports the average buy-and-hold monthly return for the Centre for Research in Security Prices value weighted and equally weighted NYSE/AMEX/NASDAQ portfolio without distribution and equally weighted portfolio of all mutual funds existing during the years with a self-declared investment objectives of growth, growth & income, income, micro-cap, small-cap, and mid-cap over time from 2004 to 2013. The gross return is estimated based on the monthly returns of the holdings of mutual funds before management fees and commissions. The CS performance, the CT performance, and the AS performance are calculated as Daniel *et al* (1997). Specifically, the CS performance is measured as the difference between the time t return of the portfolio held at time t-1 and the time t return of the time t-1 matching benchmark portfolio. The CT performance is calculated as the difference between the time t value weighted return of benchmark portfolio of stocks held at time t-1 and the time t value weighted return of benchmark portfolio of stocks held at time t-13. The AS performance is the time t value weighted return of benchmark portfolio of stocks held at time t-13. The time series average of annualized monthly returns and t-statistics are presented below (t-statistics in parentheses).

Year	CRSP VW	CRSP EW	Gross Return	CS Performance	CT Performance	AS Performance
2004	39.86%	73.82%	28.96%	0.67%	-1.15%**	28.58%
				(0.72)	(-2.27)	
2005	5.77%	4.40%	17.89%	1.86%*	-0.45%	15.63%
				(1.99)	(-1.06)	
2006	14.28%	17.28%	10.54%	-1.46%	-0.58%	12.53%
				(-1.51)	(-1.31)	
2007	5.78%	-4.53%	-2.40%	0.55%	-0.05%	-2.82%
				(0.33)	(-0.09)	
2008	-37.97%	-42.53%	-36.99%	2.95%	1.54%*	-39.02%
				(1.36)	(1.79)	
2009	31.10%	65.88%	41.87%	-6.30%	-1.74%	51.99%
				(-1.37)	(-1.20)	
2010	17.20%	24.91%	30.50%	0.75%	-0.22%	29.35%
				(0.80)	(-0.67)	
2011	-1.78%	-9.39%	6.09%	0.17%	-0.03%	5.84%
				(0.19)	(-0.05)	
2012	13.54%	14.78%	17.38%	0.52%	-0.69%	17.30%
				(0.59)	(-1.29)	
2013	27.66%	28.58%	34.38%	1.02%*	-0.86%	33.24%
				(1.72)	(-1.31)	
2004-2007	11.35%	10.89%	12.99%	0.78%	-0.42%	12.17%
				(1.51)	(-1.61)	
2007-2009	-23.68%	-18.00%	-15.84%	-2.80%	-0.03%	-13.04%
				(-0.80)	(-0.03)	
2009-2013	16.60%	18.11%	21.46%	0.43%	-0.46%*	21.06%
				(1.08)	(-1.82)	
2004-2013	7.39%	9.23%	11.29%	-0.01%	-0.37%	11.44%
				(-0.01)	(-1.57)	

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 2.4 Mutual Fund Performance in Aggregate, by Investment Objectives

This table below reports the average buy-and-hold monthly return for the Centre for Research in Security Prices value weighted and equally weighted NYSE/AMEX/NASDAQ portfolio without distribution and equally weighted portfolio of all mutual funds existing during the years with a self-declared investment objectives. The mutual funds are broken down by the CRSP investment objectives, including growth, growth & income, income, micro-cap, small-cap, and mid-cap. Panel A reports average mutual funds' performance during the whole sample period from 2004 to 2013. In order to examine the difference of mutual fund performance for time-varying market conditions, Panel B, Panel C, and Panel D presents the average performance of mutual funds for sub-sample periods from September 2004 to December 2007, from December 2007 to June 2009, and from June 2009 to December 2013. The gross return is estimated based on the monthly returns of the holdings of mutual funds before management fees and commissions. The CS performance, the CT performance, and the AS performance are calculated as Daniel *et al* (1997). Specifically, the CS performance is measured as the difference between the time t return of the portfolio held at time t-1 and the time t return of the time *t-1* matching benchmark portfolio. The CT performance is calculated as the difference between the time t value weighted return of benchmark portfolio of stocks held at time *t-1* and the time t value weighted return of benchmark portfolio of stocks held at time *t-13*. The AS performance is the time t value weighted return of benchmark portfolio of stocks held at time *t-13*. The time series average of annualized monthly returns and t-statistics are presented below (t-statistics in parentheses).

Objective	Gross Return	CS Performance	CT Performance	AS Performance
Panel A September 2004-December 2013				
All	11.29%	-0.01%	-0.37%	11.44%
		(-0.01)	(-1.57)	
Growth	10.67%	0.07%	-0.28%	10.69%
		(0.11)	(-0.95)	
Growth&Income	9.89%	-0.26%	-0.58%	10.71%
		(-0.60)	(-1.61)	
Income	9.86%	-0.21%	-0.66%	10.72%
		(-0.27)	(-1.43)	
Micro-Cap	12.19%	1.00%	-0.79%**	12.19%
		(0.85)	(-1.98)	
Small-Cap	12.97%	-0.15%	-0.40%	13.09%
		(-0.15)	(-1.12)	
Mid-Cap	12.48%	0.21%	-0.20%	12.12%
		(0.23)	(-0.74)	
Panel B September 2004-December 2007				
All	12.99%	0.78%	-0.42%	12.17%
		(1.51)	(-1.61)	
Growth	12.73%	0.03%	-0.49%	12.32%
		(0.96)	(-1.39)	
Growth&Income	11.90%	0.24%	-0.38%	11.94%
		(0.50)	(-0.73)	
Income	11.56%	-0.01%	0.22%	11.20%
		(-0.04)	(0.36)	
Micro-Cap	13.15%	2.83%**	-0.96%*	10.27%
		(2.08)	(-1.91)	
Small-Cap	13.27%	0.99%	-0.24%	11.68%
		(1.55)	(-0.78)	
Mid-Cap	15.09%	1.56%**	-0.55%***	13.36%
		(2.01)	(-3.03)	

Table 2.4 *continued*

Objective	Gross Return	CS Performance	CT Performance	AS Performance
Panel C December 2007-June 2009 (Recession)				
All	-13.04%	-2.80%	-0.03%	-13.04%
		(-0.80)	(-0.03)	
Growth	-16.57%	-1.79%	0.41%	-15.14%
		(-0.60)	(0.33)	
Growth&Income	-17.06%	-2.45%	0.05%	-14.85%
		(-1.17)	(0.04)	
Income	-16.33%	-1.67%	-0.05%	-14.78%
		(-0.45)	(-0.03)	
Micro-Cap	-17.06%	-9.47%**	-0.05%	-7.66%
		(-2.15)	(-0.03)	
Small-Cap	-13.47%	-4.60%	-0.96%	-7.90%
		(-0.89)	(-0.51)	
Mid-Cap	-15.71%	-2.75%	0.06%	-12.88%
		(-0.59)	(0.05)	
Panel D June 2009-December 2013				
All	21.46%	0.43%	-0.46%*	21.06%
		(1.08)	(-1.82)	
Growth	20.63%	0.37%	-0.37%	20.28%
		(0.68)	(-1.06)	
Growth&Income	19.78%	0.18%	-0.95%**	20.49%
		(0.57)	(-2.35)	
Income	19.60%	0.14%	-1.53%***	21.05%
		(0.18)	(-2.77)	
Micro-Cap	25.77%	3.63%***	-0.92%**	21.73%
		(3.05)	(-2.08)	
Small-Cap	23.88%	0.65%	-0.32%	22.75%
		(1.13)	(-1.14)	
Mid-Cap	22.47%	0.29%	-0.04%	21.60%
		(0.46)	(-0.14)	

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.
Note: recession during the financial crisis is defined by NBER

Table 2.5 Mutual Fund CT Performance for Buying, Sizing, and Selling

This table below reports the characteristic-timing attributes of all mutual funds The mutual funds are broken down by the CRSP investment objectives, including growth, growth & income, income, micro-cap, small-cap, and mid-cap. Panel A reports the average performance of mutual funds during the whole sample period from 2004 to 2013. Panel B, Panel C, and Panel D presents the average performance of mutual funds for sub-sample periods from September 2004 to December 2007, from December 2007 to June 2009, and from June 2009 to December 2013. The aggregate CT performance (CT) is calculated as the difference between the time t value-weighted return of benchmark portfolio of stocks held at time *t-1* and the time t value weighted return of benchmark portfolio of stocks held at time *t-13*. The aggregate CT performance is decomposed into three components for buying, sizing, and selling, based on the changes in shares held between two reports. CT_{buy} measures the monthly characteristic-timing performance at time *t* when mutual funds increase holdings of stocks at time *t-1*; CT_{size} measures the monthly characteristic-timing performance at time t when mutual funds remain the same holdings of stocks at time *t-1*; CT_{sell} measures the monthly characteristic-timing performance at time t when mutual funds decrease holdings of stocks at time *t-1*. The time series average of annualized monthly returns and t-statistics are presented below (t-statistics in parentheses).

	All Funds	Growth	Growth &Income	Income	Micro-Cap	Small-Cap	Mid-Cap
Panel A September 2004-December 2013							
$\boldsymbol{CT}$	-0.37%	-0.28%	-0.58%	-0.66%	-0.79%*	-0.40%	-0.20%
	(-1.57)	(-0.95)	(-1.61)	(-1.43)	(-1.98)	(-1.12)	(-0.74)
$\boldsymbol{CT_{buy}}$	1.42%*	1.39%*	1.02%	0.86%	1.48%	1.67%	1.69%*
	(1.65)	(1.71)	(1.41)	(1.54)	(1.43)	(1.58)	(1.77)
$\boldsymbol{CT_{size}}$	-0.02%	0.06%	-0.04%	-0.20%	-0.37%*	-0.15%	0.09%
	(-0.24)	(0.62)	(-0.30)	(-0.75)	(-1.89)	(-1.29)	(0.76)
$\boldsymbol{CT_{sell}}$	-1.78%*	-1.73%**	-1.57%**	-1.48%**	-1.95%	-1.94%	-1.96%*
	(-1.86)	(-1.89)	(-2.14)	(-2.30)	(-1.53)	(-1.58)	(-1.84)
Panel B September 2004-December 2007							
$\boldsymbol{CT}$	-0.42%	-0.49%	-0.38%	0.22%	-0.96%*	-0.24%	-0.55%***
	(-1.61)	(-1.39)	(-0.73)	(0.36)	(-1.91)	(-0.78)	(-3.03)
$\boldsymbol{CT_{buy}}$	2.08%**	2.15%**	1.80%**	1.33%**	1.71%	2.16%	2.36%*
	(1.97)	(2.21)	(2.23)	(2.07)	(1.16)	(1.54)	(1.84)
$\boldsymbol{CT_{size}}$	0.04%	0.05%	0.06%	0.26%	-0.30%	-0.07%	0.16%
	(0.43)	(0.42)	(0.32)	(0.93)	(-1.27)	(-0.76)	(1.49)
$\boldsymbol{CT_{sell}}$	-2.53%**	-2.67%***	-2.23%***	-1.41%**	-2.47%	-2.35%	-3.02%**
	(-2.2)	(-2.58)	(-2.71)	(-2.05)	(-1.26)	(-1.48)	(-2.21)
Panel C December 2007-June 2009 (Recession)							
$\boldsymbol{CT}$	-0.03%	0.41%	0.05%	-0.05%	-0.05%	-0.96%	0.06%
	(-0.03)	(0.33)	(0.04)	(-0.03)	(-0.03)	(-0.51)	(0.05)
$\boldsymbol{CT_{buy}}$	-2.29%	-2.56%	-2.29%	-1.13%	-1.34%	-2.10%	-2.24%
	(-0.64)	(-0.75)	(-0.73)	(-0.51)	(-0.32)	(-0.48)	(-0.59)
$\boldsymbol{CT_{size}}$	0.01%	0.12%	0.23%	0.12%	-0.09%	-0.41%	0.08%
	(0.04)	(0.34)	(0.38)	(0.10)	(-0.11)	(-0.69)	(0.15)
$\boldsymbol{CT_{sell}}$	2.24%	2.88%	2.18%	0.86%	1.41%	1.48%	2.23%
	(0.52)	(0.72)	(0.68)	(0.29)	(0.27)	(0.26)	(0.47)
Panel D June 2009-December 2013							
$\boldsymbol{CT}$	-0.46%*	-0.37%	-0.95%**	-1.53%***	-0.92%**	-0.32%	-0.04%
	(-1.82)	(-1.06)	(-2.35)	(-2.77)	(-2.08)	(-1.14)	(-0.14)
$\boldsymbol{CT_{buy}}$	2.28%**	2.29%**	1.66%**	1.23%**	2.34%**	2.68%**	2.63%**
	(2.39)	(2.52)	(2.06)	(1.77)	(2.00)	(2.31)	(2.38)
$\boldsymbol{CT_{size}}$	-0.07%	0.05%	-0.22%	-0.65%**	-0.52%**	-0.12%	0.04%
	(-0.72)	(0.33)	(-1.21)	(-2.39)	(-2.44)	(-1.02)	(0.28)
$\boldsymbol{CT_{sell}}$	-2.64%***	-2.65%***	-2.40%***	-2.36%***	-2.74%**	-2.84%**	-2.64%**
	(-2.62)	(-2.63)	(-2.98)	(-3.40)	(-2.11)	(-2.39)	(-2.41)

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 2.6 Mutual Fund Characteristic-Timing Performance Persistence

This table presents the persistence of mutual fund characteristic-timing performance. The aggregate CT performance (CT) is calculated as the difference between the time t value-weighted return of benchmark portfolio of stocks held at time *t-1* and the time *t* value weighted return of benchmark portfolio of stocks held at time *t-13*. The aggregate CT performance is decomposed into three components for buying, and selling, based on the changes in shares held between two reports. CT_{buy} measures the monthly characteristic-timing performance at time t when mutual funds increase holdings of stocks at time *t-1*while CT_{sell} measures the monthly characteristic-timing performance at time t when mutual funds decrease holdings of stocks at time *t-1*. At the end of each quarter, all existing mutual funds are divided into five quintiles based on the average monthly aggregate, buying, and selling characteristic-timing performance. The characteristic-timing performance for the formation quarter and subsequent four quarters are reported. All returns are annualized monthly returns. Numbers in parentheses are t-statistics, which are computed based on two-way clustered standard errors.

Current Quarter Performance Quintiles	Quarters				
	Q+0	**Q+1**	**Q+2**	**Q+3**	**Q+4**
Panel A: Aggregate CT Performance					
q1 (Loser)	-7.64%***	-0.87%***	-0.46%	-0.87%***	-0.75%***
	(-16.25)	(-2.74)	(-1.37)	(-3.46)	(-3.03)
q2	-2.80%***	-0.48%**	-0.45%*	-0.64%**	-0.50%**
	(-12.46)	(-2.33)	(-1.90)	(-3.04)	(-1.96)
q3	-0.44%**	-0.35%	-0.34%	-0.30%	-0.37%
	(-2.23)	(-1.58)	(-1.52)	(-1.50)	(-1.49)
q4	1.99%***	-0.21%	-0.46%*	-0.25%	-0.23%
	(7.13)	(-0.75)	(-1.95)	(-0.94)	(-0.98)
q5 (Winner)	7.26%***	-0.10%	-0.41%	-0.09%	-0.15%
	(12.74)	(-0.24)	(-1.32)	(-0.25)	(-0.58)
q5-q1	16.02%***	0.77%*	0.05%	0.78%*	0.61%**
	(15.78)	(1.72)	(0.1)	(1.84)	(2.31)
Panel B: Buying CT Performance					
q1 (Loser)	-5.69%***	1.00%	1.53%	1.36%	1.41%*
	(-4.69)	(0.99)	(0.76)	(1.44)	(1.73)
q2	-0.94%	1.17%	1.25%*	1.24%	1.27%*
	(-1.28)	(1.52)	(1.74)	(1.54)	(1.73)
q3	1.23%**	1.32%**	1.29%*	1.44%*	1.16%
	(1.91)	(1.96)	(1.79)	(1.95)	(1.56)
q4	3.71%***	1.56%**	1.48%*	1.52%**	1.40%*
	(5.40)	(2.10)	(1.91)	(2.07)	(1.71)
q5 (Winner)	10.00%***	2.39%**	1.85%*	1.94%**	1.67%
	(9.39)	(2.42)	(1.85)	(2.1)	(1.58)
q5-q1	16.54%***	1.38%*	0.31%	0.58%	0.26%
	(12.87)	(1.68)	(0.56)	(0.99)	(0.48)
Panel C: Selling CT Performance					
q1 (Loser)	-10.05%***	-2.83%***	-2.28%**	-2.56%**	-2.14%*
	(-9.40)	(-2.69)	(-2.13)	(-2.57)	(-1.83)
q2	-4.16%***	-1.89%**	-1.80%**	-2.04%**	-1.71%*
	(-5.65)	(-2.37)	(-2.12)	(-2.45)	(-1.85)
q3	-1.60%**	-1.54%*	-1.67%**	-1.70%**	-1.61%**
	(-2.27)	(-1.94)	(-2.08)	(-2.04)	(-1.93)
q4	0.84%	-1.51%	-1.65%*	-1.58%*	-1.60%*
	(1.02)	(-1.80)	(-2.01)	(-1.80)	(-1.97)
q5 (Winner)	6.06%***	-1.44%	-1.90%*	-1.55%	-1.74%*
	(4.21)	(-1.28)	(-1.88)	(-1.45)	(-1.92)
q5-q1	17.74%***	1.43%*	0.38%	1.02%	0.42%
	(13.02)	(1.71)	(0.68)	(1.59)	(0.77)

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 2.7 The Performance of High vs. Low Style Drift

This table below presents the subsequent gross return, the CS performance, the CT performance, and the AS performance following different levels of active style drift. The gross return is estimated based on the monthly returns of the holdings of mutual funds before management fees and commissions. The CS performance, the CT performance, and the AS performance are calculated as Daniel et al (1997). Specifically, the CS performance is measured as the difference between the time t return of the portfolio held at time t-1 and the time t return of the time t-1 matching benchmark portfolio. The CT performance is calculated as the difference between the time t value weighted return of benchmark portfolio of stocks held at time t-1 and the time t value weighted return of benchmark portfolio of stocks held at time t-13. The AS performance is the time t value weighted return of benchmark portfolio of stocks held at time t-13. At the end of each quarter, all existing mutual funds with self-declared investment objectives including growth, growth & income, income, micro-cap, small-cap, and mid-cap are ranked and divided into five quintiles based on the level of active style drift. Then average measures of performance calculated for each of quintile groups of fund portfolio at the end of each month. The time series average of annualized monthly returns and t-statistics are presented below (t-statistics in parentheses).

Active Style Drift Quintiles	**Gross Return**	**CS Performance**	**CT Performance**	**AS Performance**
Top 20%	10.89%	0.07%	-0.66%**	11.54%
	-	(0.09)	(-2.31)	-
2nd 20%	11.66%	0.04%	-0.23%	11.64%
	-	(0.07)	(-0.88)	-
Mid 20%	11.32%	0.35%	-0.16%	11.00%
	-	(0.61)	(-0.59)	-
4th 20%	10.84%	-0.28%	-0.24%	11.22%
	-	(-0.52)	(-0.79)	-
Bottom 20%	10.68%	-0.07%	-0.57%*	11.15%
	-	(-0.14)	(-1.80)	-
Top-Bottom 20%	0.21%	0.13%	-0.08%	0.39%
	-	(-0.28)	(0.26)	-
Top-Mid 20%	-0.43%	-0.28%	-0.49%*	0.54%
	-	(0.66)	(-1.67)	-
Bottom-Mid 20%	-0.64%	-0.42%	-0.41%*	0.15%
	-	(-1.31)	(-1.95)	-

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 2.8 The Characteristic-Timing Performance of High vs. Low Style drift for Buying and Selling

This table below presents the subsequent the CS performance and the CT performance following different levels of active style drift. The CS performance and the CT performance are calculated as Daniel *et al* (1997). Specifically, the CS performance is measured as the difference between the time t return of the portfolio held at time t-1 and the time t return of the time t-1 matching benchmark portfolio. The CT performance is calculated as the difference between the time t value weighted return of benchmark portfolio of stocks held at time t-1 and the time t value weighted return of benchmark portfolio of stocks held at time t-13. The aggregate CT performance is decomposed into three components for buying, sizing, and selling, based on the changes in shares held between two reports. $\mathbf{CT_{Buy}}$ measures the monthly characteristic-timing performance at time t when mutual funds increase holdings of stocks at time t-1; $\mathbf{CT_{Sell}}$ measures the monthly characteristic-timing performance at time t when mutual funds decrease holdings of stocks at time t-1. At the end of each quarter, all existing mutual funds with self-declared investment objectives including growth, growth & income, income, micro-cap, small-cap, and mid-cap are ranked and divided into five quintiles based on the level of active style drift. Then average measures of performance calculated for each of quintile groups of fund portfolio at the end of each month. The time series average of annualized monthly returns and t-statistics are presented below (t-statistics in parentheses).

Active Style Drift Quintiles	**Aggregate CT**	$\mathbf{CT_{Buy}}$	$\mathbf{CT_{Sell}}$
Top 20%	-0.66%**	2.01%	-2.97%*
	(-2.31)	(1.34)	(-1.87)
2nd 20%	-0.23%	1.7%*	-2.18%**
	(-0.88)	(1.91)	(-2.21)
Mid 20%	-0.16%	1.23%*	-1.31%*
	(-0.59)	(1.72)	(-1.72)
4th 20%	-0.237%	1.03%*	-1.22%**
	(-0.79)	(1.88)	(-2.01)
Bottom 20%	-0.57%*	0.48%	-1.00%**
	(-1.80)	(1.11)	(-2.05)
Top-Bottom 20%	-0.08%	1.52%	-1.98%*
	(0.26)	(1.39)	(-1.72)

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Chapter 3

Good Buyers and Good Sellers? :

Fund Manager Trading Motivations and Characteristic-Timing Performance

3.1 Introduction

Open-end equity mutual funds provide investment expertise, well diversified equity positions and a great deal of liquidity to their clients. Retail fund investors can actively buy and redeem fund shares without paying a large premium for immediate liquidity needs. However, this provision of low cost liquidity can force fund managers to make uninformed trading in response to fund flows.[1] The literature has theoretically indicated that liquidity-motivated trading can have a significant adverse effect on fund performance, when liquidity-motivated trading is considered in a rational expectations framework.[2] In particular, Grossman and Stiglitz (1980) suggest that in a rational expectation world with costly information production, equilibrium can be attained only when liquidity-motivated traders sustain losses to informed traders to compensate the informed traders' cost of information processing. These theoretical models predict that fund managers who are forced to engage in a material volume of liquidity-driven

[1] See e.g., Chordia (1996), Edelen (1999), and Nanda *et al* (2000).
[2] See e.g., Grossman (1976); Hellwig (1980); and Verrcecchia (1982).

trading will inevitably experience underperformance, even if these fund managers are informed.

Nevertheless, the majority of empirical studies in the prior literature overlook the fact that open-end mutual fund managers often engage in flow-induced trading, and thus the conventional analysis used in these studies can yield misleading inferences regarding fund manager skill. Indeed, by using a conditional benchmark that control for the time varying expected market returns, Ferson and Schadt (1996) and Ferson and Warther (1996) show that the "perverse" market timing ability for mutual fund managers is removed. Given the positive correlation between aggregate fund flows and time varying expected market returns, these authors suggest that fund flow is the source of negative market timing performance documented in the literature. Edelen (1999) is the first attempt to directly examine the potential impact of fund flows on performance at individual fund level and the author finds a negative relationship between volume of liquidity-motivated trading and fund risk-adjusted performance, which questions the common finding of fund manager underperformance in previous studies. After controlling for the adverse effect of fund flows, Edelen (1999) finds favourable evidence for fund managers when compared to standard performance tests.

These studies, however, are subject to some criticisms. First, the number of funds in their studies is relatively small (at most 166) when compared to other studies on fund performance. Second, these studies employ the return-based regression approach of Treynor and Mazuy (1966) and Henriksson and Merton (1981). This return-based approach is subject to the "artificial timing" bias that might arise when the non-linear relationship between fund returns and market return can be induced by factors other than active marking timing actions (e.g., Jagannathan and Korajczyk, 1986). This approach also implicitly assumes that fund managers tend to time the market in a specific way but in practice this is not necessarily true since fund managers can implement timing strategies in a more complicated way. Third, these studies examine the effect of fund flows on fund performance in aggregate, and thus they are not able to condition timing performance on the direction and magnitude of fund flows.

This chapter attempts to address these criticisms and to advance the investigation of the effect of fund flows on fund performance and trading decisions. The number of firms in my dataset is more than twenty times the number in the dataset used by Ferson and Schadt (1996), Ferson and Warther (1996), and Edelen (1999). There are 3384 unique actively managed mutual funds in my sample from 2003 to 2009, obtained from the CRSP Mutual Fund Holdings Database. I address the model mis-specification issue by using the "characteristic-timing" performance (CT) of Daniel *et al* (1997). The CT measure directly looks at whether changes in portfolio weights of size, book-to-market and momentum factors forecast future returns, which allows researchers to avoid the biases in the return-based approach.

In the first half of this chapter, I consider the potential adverse effect of fund flows on fund performance by segmenting fund portfolios based on net realised fund flows. The hypothesis that fund flows have an adverse effect on fund performance finds strong support and the common conclusion of underperformance changes when consideration is given to the liquidity provision of mutual funds. This chapter shows, mutual fund managers exhibit significantly negative characteristic-timing performance only when they experience significant fund inflows. In a further refinement, mutual funds within each flow quintile are sorted and categorised into another 5 quintile groups, on the basis of fund manager conviction to make discretionary timing decisions (i.e., active style drift). The rationale is that fund managers' portfolios can diverge from their target exposure to the three stock characteristic styles due to unanticipated fund flows.

However, fund managers can proportionally expand or reduce current stock holdings to maintain their intended risk exposure and control liquidity. They will actively engage in style drift towards the three stock characteristics when and only when they have strong valuation beliefs about future performance. In this case, one should observe a positive relationship between the magnitude of style bets and style-timing performance when experiencing fund flow shocks. Strikingly, this chapter reveals that when fund managers experience significant inflows, large style bets measured by active style drift are associated with an average negative characteristic-timing return of -1.76% per year (t-statistic=-2.78). A weaker relationship is also found for fund managers who face significant outflows. These results suggest that the inferior timing performance is not entirely driven by the detrimental effects of fund flows, but at least partly due to negative timing ability of fund managers. Overall, this chapter shows that fund managers on average are not able to time risk factors.

Given the fact that the liquidity providing role of mutual funds can cause fund managers to act as uniformed liquidity traders, existing studies that do not account for funds' flow-induced trading activities can yield negatively biased inferences regarding fund managers' ability (e.g., Edelen, 1999; Alexander *et al*, 2007). For instance, by examining a sample of "star" growth oriented mutual funds, Chen *et al* (2013) show that superior performing fund managers exhibit significant timing ability when buying stocks but negative performance when selling stocks. However, one major limitation of Chen *et al* (2013)'s study is that the authors give no consideration to liquidity-induced trades potentially imposing significant indirect trading costs. Thus, the lack of positive unconditional selling performance in Chen *et al* (2013)'s study can merely reflect the negative net effect between cost of liquidity provision and characteristic-timing return of fund managers' selling decisions. In fact, the adverse effect of fund flows on sell decisions can be particularly severe because when experiencing significant outflows, fund managers without enough cash reserves have no other options available but to sell their assets immediately at fire sale prices (Coval and Stafford, 2007; Zhang, 2010). Thus, whether and how far differential trading abilities can be driven by the adverse effect of liquidity-motivated trading remains unclear.

The second half of this chapter continues the investigation of fund managers' distinct trading skills by relating the performance of mutual fund trades to the motivation for making these trades. In order to separate valuation-based trades from liquidity-motivated trades, this chapter follows the approach of Alexander *et al* (2007) to condition trades on the direction and magnitude of concurrent realised net fund flows. The rationale is that fund managers who face severe outflows would buy stocks that are perceived to be significantly undervalued and thus a larger proportion of the purchases they make in their portfolios are likely to be motivated by valuation beliefs. On the other hand, when experiencing significant inflows, fund managers are compelled to work off excess cash, and thus a smaller proportion of the purchases in their portfolios are likely to be valuation-based ones. Symmetrical intuition applies to fund managers' sales of stocks. If mutual fund managers have characteristic-timing ability, valuation-based purchases (sales) should have higher characteristic-timing returns than liquidity-based purchases (sales) would have.

Indeed, my results indicate that the performance of mutual fund trades is significantly related to the motivation behind fund managers' trading decisions. Valuation-motivated buys are associated with subsequent characteristic-timing returns of 1.90% per year (t-statistics=2.19), while liquidity-induced purchases are associated with no significant characteristic-timing performance, suggesting that fund managers are not able to time stock characteristics from their buying activities when compelled to work off excessive liquidity from investor inflows. On the other hand, valuation-motivated sales significantly outperform liquidity-driven sales by an average of 0.69% per year at the 5% significance level. However, valuation-motivated sales, which should purely represent fund managers' beliefs about future stock performance, are still associated with negative characteristic-timing returns of -1.57% per year (t-statistics=1.94), which is consistent with the expectation that fund managers are not able to generate characteristic-timing performance from their selling decisions. These results are robust when using multivariate regressions to control for other mutual fund characteristics that might be related to the performance of fund trades. Further investigation focusing on fund trades at the individual stock level shows consistent findings that valuation-based trades outperform liquidity-driven trades by a statistically and economically significant amount.

Most studies on mutual fund performance view fund managers as a homogeneous class of professional investors, and to the best of my knowledge, the literature has not yet explored whether different groups of fund managers possess different skills. A group of fund managers might specialize in buying decisions and another group of fund managers might be expert at selling decisions, or a small subset of fund managers might successfully perform both buying and selling tasks. In particular, since selling decisions are susceptible to behavioural biases and heuristics, fund managers who can manage to make sell decisions in a more disciplined and research-based way may be more likely to possess general investment ability. This idea leads this chapter to identify skilled fund managers using an approach that is different from the typical approach that is based on total fund performance in the literature. Specifically, I identify the top 25% of funds who have best historical records of characteristic-timing returns when selling stocks as "good sellers". I then regress characteristic-timing performance from buying activities on a "good sellers" indicator to investigate if these fund managers can successfully perform both buying and selling tasks and generate superior aggregate performance. Similarly, I select the top 25% of mutual fund maangers in terms of their characteristic-timing ability when buying stocks and determine if these "good buyers" have significant selling performance.

This chapter provides strong evidence to show that different groups of fund managers possess different skills. After controlling for fund characteristics and time fixed effects, "good sellers" outperform other mutual funds when selling stocks, by a significant average of 1.35% per year and they also significantly outperform other fund managers when purchasing stocks by an average of 0.87% per year. On the other hand, "good buyers" exhibit superior characteristic-timing performance when adding stocks into their portfolios. There is a statistically and economically significant outperformance of 3.75% per year. This is true by construction. Strikingly, this group of "good buyers" insignificantly underperforms other funds by an average of 0.13% per year when selling stocks. Furthermore, "good sellers" exhibit a statistically and economically significant outperformance of 0.31% per year in aggregate characteristic-timing performance, while "good buyers" have no significant aggregative performance. Overall, these results indicate that there are a small number of mutual fund managers who possess both buying and selling abilities. More interestingly, my findings are consistent with the notion that sell decisions are particularly susceptible to behavioural biases and heuristics, and are not able to be made as disciplined as buying decisions would be.

This chapter is closely related to a number of recent studies looking at the structure of open-end mutual funds such as Chordia (1996), Edelen (1999) and Nanda *et al* (2000). These studies argue that one of the major services mutual fund managers offer is to provide liquidity to fund investors, but this provision of liquidity imposes significant indirect trading costs on mutual funds, as reflected in the negative relationship between fund performance and investors flows. While Ferson and Schadt (1996) and Ferson and Warther (1996) suggest that negative market timing is attributable to fund flows, Edelen (1999) provides direct evidence to show that the common finding of negative performance at open-end mutual funds is driven by the costs of liquidity-induced trading. This chapter complements their findings with direct evidence that liquidity trades have an adverse effect on fund performance by looking at characteristic-timing returns using the holdings of a large sample of mutual funds.

Edelen (1999) measures the adverse effect of fund flows in aggregate and suggest that fund managers exhibit negative timing ability when they have to deal with flows. My results make an incremental contribution over and above Edelen (1999)'s findings by showing that the adverse effect of fund flows on timing performance arises mainly in the case of significant fund inflows. Mutual fund managers in my sample exhibit negative timing performance only when experiencing significant fund inflows. In particular, large style bets made by fund managers who have significant inflows are associated with significant underperformance. These results suggest that fund managers are not able to make use of the financial flexibility provided by fund inflows, but instead, excessive cash holdings act as a significant drag on fund performance, which is consistent with the free cash flow hypothesis that managers tend to use their free cash flows to invest in negative NPV projects, which is well documented in corporate finance literature.[3]

[3] See e.g., Jensen (1986), Stulz (1990), and others.

By considering the detrimental effect of flow-induced trading on performance, this chapter provides strong evidence that directly supports the conclusion that fund managers have distinct trading skills in terms of their characteristic-timing ability. First, although the academic literature recognises that liquidity-induced trades are costly, there are few empirical studies that directly investigate the costs of liquidity provision on actual fund trades. One notable exception is Alexander *et al* (2007) who place emphasis on fund managers' stock picking ability and show that valuation-motivated trades outperform liquidity-driven trades. This chapter contributes to the literature by showing that trade motivation also matters for characteristic-timing ability, even after controlling for fund characteristics and time fixed effects. Second, my results show that fund managers appear to exhibit significantly negative characteristic-timing performance from their selling decisions, even when most of these sales are motivated by fund managers' valuation beliefs. Third, this chapter contributes to the literature by showing that a small subset of fund managers who specialise in making sell decisions (good sellers) also possess buying skill and exhibit superior aggregate performance. However, those who have the best record of buying performance (good buyers) exhibit negative selling ability. My results suggest that the performance deriving from fund managers' selling activities is a more powerful indicator of fund manager skills.

The remainder of this study is organized as follows. Section 3.2 summarizes recent studies investigating mutual fund flows and the relationship between mutual fund flows and fund manager timing ability. Section 3.3 describes the related methodology used in the paper. Section 3.4 presents the data source and sample construction. Section 3.5 shows the results and discusses the findings and Section 3.6 concludes.

3.2 Literature Review

This section first reviews recent empirical studies that investigate the relationship between fund performance and investors flows. I then briefly review selected theoretical studies on rational expectation models for trading and the implication of these models for fund investors' behaviours and fund performance. Lastly, I review empirical studies that investigate the impact of fund flows on fund performance.

The mutual fund industry is a natural laboratory to study the behaviours of individual investors who trade fund shares and the behaviour of mutual fund managers who compete with their peer managers for investor inflows. The majority of previous studies in the literature place emphasis on understanding the relationship between individual investors' fund flows and fund characteristics. In particular, one of the most salient findings is the response of fund investors to mutual fund performance. A number of early papers demonstrate a general positive linear relationship between fund flows and performance of individual funds (e.g., Spitz, 1970; Smith, 1978). Patel, Zeckhauser, and Hendricks (1991) report a positive linear relationship between a funds' annual dollar growth and both its size and ranked performance using raw returns. Kane, Santini, and Aber (1991) detect a similar positive relationship between quarterly percentage growth and fund performance measured by excess returns, Sharpe ratios and Jensen's alphas.

Later studies advance the investigation and call attention to a potential non-linear relationship between past fund performance and investor flows. For example, Ippolito (1992) finds that the effect of past performance on fund growth is greater for funds that generate positive excess returns using the market model, compared to those that have negative abnormal returns. The author argues that allocating monies to past winner funds is rational investor behaviour in financial markets with acute information asymmetry. By using piecewise linear regression, Sirri and Tufano (1998) directly examine differential investor responses to past fund performance relative to other funds in the same market segment, and confirm that fund flows are sensitive to historical performance but the sensitivity is non-linear: investors appear to rush into funds with high prior performance, but fail to flee from funds that have performed poorly.

This convex performance-flow relationship can potentially create fund manager incentives to take action to maximise their own benefits at the expense of fund investors. For example, Chevalier and Elison (1997) document the fact that superior performance attracts more cash flow into funds, while poor returns do not lead to a symmetrically adverse consequence. These authors take this non-linear performance-flow relationship further, to explain the tendency of fund managers to alter the riskiness of their portfolios.

Given this performance-flow relationship, it is entirely natural to ask whether fund investors have ability to identify superior performing funds. There is a line of research on the relationship between fund flows and subsequent fund performance. Despite the poor aggregate returns to the mutual fund industry, Gruber (1996) argues that new money flowing into the industry must be able to outperform existing assets, and the author finds that fund investors exhibit fund-selection skill and investors' money is "smart" enough to flow into those funds that have a better chance of superior subsequent performance. This "smart money" effect also finds strong support from Zheng (1999), who examines a large sample of 1826 funds from 1970 to 1993. Zheng (1999) finds that fund managers who receive higher fund inflows perform significantly better than those who experience outflows. Sapp and Tiwari (2004) demonstrate the "smart money" effect is explained by stock return momentum over the short term. Opposite to the "smart money" effect, Frazzini and Lamont (2006) use mutual fund flows as a measure of individual investor sentiment and show that high sentiment predicts low future performance at the individual stock level. These authors report that investors tend to direct their money to mutual funds which invest in stocks that do poorly over the subsequent few years, and they argue that investor flows are "dumb money" and retail investors significantly reduce their wealth in the long run by actively reallocating their money across mutual funds. This "dumb money" effect dominates at longer horizons.

Another large body of recent studies pays attention to the implications of fund flows for asset pricing. For instance, Coval and Stafford (2007) show that mutual fund managers tend to expand their existing holdings when experiencing capital inflows but sell down their position to fulfil redemption requests, and they find that such flow-driven trading can drive individual stock prices temporarily away from fundamental value. Lou (2012) proposes a flow-based mechanism to explain well-known empirical patterns of return predictability, including short term fund performance persistence, the "smart money" effect, and stock price momentum. Persistent investor inflows drive past winning funds to collectively invest new capital into their existing holdings (particularly past winning stocks), while outflows force past losing funds to collectively liquidate their positions (particularly past losing stocks). In the end, predictable price pressure from fund flows leads past winning stocks to keep outperforming past losing stocks, and thus past winning funds to continue to outperform past losing funds. Similar to other work investigating stock price pressure from investor flows, these studies express the concern that flow-induced trading can adversely affect fund performance.

Indeed, the literature has theoretically shown that liquidity-motivated trading can have a significant adverse effect on fund performance, when liquidity-motivated trading is considered in a rational expectation framework.[4] In particular, Grossman and Stiglitz (1980) construct a model in which the market is not perfect: prices do not perfectly reflect the underlying information, so that those who invest resources in collecting information can receive compensation. In other words, the authors suggested that in a rational expectation world with costly information acquisition, equilibrium can be attained only when liquidity-motivated traders sustain losses to informed traders to compensate the informed traders' cost of information processing. Thus, fund managers who are forced to engage in a material volume of liquidity-driven trading will inevitably experience underperformance, even if these fund managers are informed.

A number of empirical studies question the common findings of mutual fund underperformance in the literature. For example, Ferson and Schadt (1996) demonstrate that by using a conditional benchmark that controls for time-varying expected market returns, "perverse" market timing is removed. Ferson and Warther (1996) further this and document a positive correlation between aggregate fund flows and lagged instruments for time-varying expected market returns, indicating that negative market timing is attributable to fund flows. However, none of these studies directly examines the relationship between market-timing performance and fund flows.

Edelen (1999) argues that one reason early studies fail to detect the market timing ability of fund managers is that their analysis gives no consideration to the fact that fund managers provide investors with a great deal of virtually free liquidity that can

[4] See e.g., Grossman (1976); Hellwig (1980); and Verrcecchia (1982).

impose substantial indirect costs on fund performance. By examining 166 open-end mutual funds from 1985 to 1990, Edelen (1999) show that after controlling for the adverse effect of flow-induced trading, mutual fund managers do add value to portfolios by about one and one-half percent per year. More interestingly, based on the positive relationship between aggregate fund flows and market returns found by Warther (1995) and Edelen and Warner (1998), Edelen (1999) argues that such a positive correlation between fund flows and market returns can give rise to the negative market timing documented in the literature. To investigate the link between market timing performance and the volume of fund flows, Edelen (1999) adds an additional market-timing regressor that interacts with fund flows in the traditional market timing models of Treynor and Mazuy (1966) and Henriksson and Merton (1981), and finds that the interactive regressor explains all of the negative market timing relationship, indicating that fund managers exhibit negative market timing ability when and only when they experience fund flows.

Based on the insight that liquidity-induced trades have an adverse effect on fund performance, a recent work by Alexander *et al* (2007) relate the performance of mutual fund trades to their motivation. These authors show strong evidence that valuation-motivated trades have significantly higher benchmark-adjusted returns then liquidity-motivated trades More importantly, Alexander *et al* (2007) provide a more powerful test of mutual fund managers' ability to value stocks by controlling for the motivation of their trades. They argue that if trading motivation matters in terms of subsequent performance, a more accurate indicator of mutual fund managers' abilities should be based on the trades that are made based on their beliefs about future stock performance, not for other reasons.

To summarise, it is now widely accepted that retail fund investors view historical fund performance as an important signal of fund manager investment skills, and thus tend to rush into funds with good past performance and fail to flee from funds with poor past performance. There is a large body of studies in the literature that seeks to understand this convex performance-flow relationship and its implication for fund manager behaviour and asset pricing. Recent papers point out that mutual fund managers provide a great deal of liquidity to fund investors, and researchers argue that this provision of liquidity can impose significant indirect trading costs on fund managers. This calls attention to the common finding of fund manager underperformance documented in the literature, because the conventional analysis ignores the adverse effect of liquidity-induced trades and therefore might lead to an incorrect inference about fund manager skills. However, little attention to date has been paid to examining the direct effect of fund flows on fund trade performance.

3.3 Methodology

3.3.1 Measuring Characteristic-Timing Performance

The "characteristic timing" measure of Daniel *et al* (1997) allows researchers to capture fund performance driven by fund managers' ability to time the three different investment styles of size, book-to-market, and momentum. Unlike factor-based methods, this characteristic measure of timing performance directly looks at whether changes in the relative portfolio weights of these styles can forecast future returns. The *CT* for month *t* measure is defined as:

$$CT_t = \sum_{j=1}^{N} (\tilde{\omega}_{j,t-1} \tilde{R}_t^{b_{j,t-1}} - \tilde{\omega}_{j,t-13} \tilde{R}_t^{b_{j,t-13}}) \quad (1)$$

where $\widetilde{\omega}_{j,t-1}$ is the portfolio weight of stock j at the end of month *t-1*, $\widetilde{\omega}_{j,t-13}$ is the portfolio weight of stock j at the end of month *t-13*, $\tilde{R}_t^{b_{j,t-1}}$ is the month t return of the characteristic-based passive benchmark portfolio that is matched to individual stock *j* according its size, book to market and momentum during the month *t-1*, $\tilde{R}_t^{b_{j,t-13}}$ is the month *t* return of the characteristic-based benchmark portfolio that is matched to stock *j* during month *t-13*. To illustrate the rationale behind the *CT* measure, suppose that a fund increases its weight in high book-to-market stocks at the beginning of the month in which the book-to-market effect is unusually strong, then this fund would have positive *CT* performance for that month. A significant positive time series average of the *CT* measure of a fund indicates superior characteristic-timing ability by this fund.

This characteristic-based approach requires the construction of passive benchmark portfolios that are matched to individual stocks in the mutual fund portfolios with the dimensions of market value of equity (size), book-to-market ratio (btm), and momentum effect (mom). This paper constructs passive benchmark portfolios according to the procedure detailed in Daniel *et al* (1997). Briefly, at the end of June each year, the common stocks listed from the NYSE, AMEX, and NASDAQ are categorized into three quintile groups based on individual stock size, book to market ratio and prior year return and consequently $5 \times 5 \times 5$ sorted characteristic-based portfolios are formed. The monthly returns of these benchmark portfolios are calculated as the monthly value weighted returns of the stocks in the 125 portfolios. The detailed procedure is provided in Daniel *et al* (1997).

3.3.2 Measuring Buying and Selling Performance

Chen *et al* (2013) point out that the traditional *CT* measure, which is simply calculated by aggregating the characteristic timing performance of all holdings, would mask the distinct characteristic timing ability of buying and selling. This chapter follows Chen *et al* (2013) in decomposing the aggregate CT performance into different trading components. Specifically, for each fund, I measure the changes in number of shares held in each stock from the end of quarter *t-1* to the end of quarter *t* for each quarter in the sample period. Increases in the number of shares are treated as buys and aggregated to form the buy portfolio, and decreases are aggregated to form the sell portfolio, for each fund each quarter. This chapter then calculates the characteristic-timing performance for each trading portfolio.

3.3.3 Estimating 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:

$$FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}}{TNA_{i,t-1}} \tag{2}$$

where $TNA_{i,t}$ is the total net assets for individual fund share class *i* at time t; $RET_{i,t}$ is the gross return before expense ratio for individual fund share class *i* at time t; $MGN_{i,t}$ is the increase in total net assets for individual fund share class *i* at time t due to fund mergers. Since the CRSP Mutual Fund Database does not provides the exact date on which fund mergers occur, this paper follows Lou (2012) and uses 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 matching period of 7 months. 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 inflows and outflows take place at the end of each quarter, and investors reinvest their dividends and capital appreciation distributions in the same fund.

3.3.4 Measuring Trade Motivation

To measure trade motivation, this paper follows Alexander *et al* (2007) and divides fund manager trading activities into different types and track the characteristic-timing performance of trades, based on the various motivations driving them. Specifically, for each fund *i*, trade in stock *j* made by the fund manager is estimated as the change in the number of shares held in stock *j* between two consecutive reports from time *t-1* and time *t* in the sample period and trade dollar volume for each stock *j* is calculated by multiplying each change by the appropriate stock price which is the average daily closing stock price between the two consecutive report dates when the trade is assumed to occur. Trades associated with increased number of shares are treated as buys and then summed to obtain total purchase volume $BUY_{i,t}$for fund *i* at time *t* and trades associated with decreased number of shares are aggregated to form the total sell volume $SELL_{i,t}$ for fund *i* at time t. Buy flow score ($BF_{i,t}$) and sell flow score ($SF_{i,t}$) that are used as proxies for trade motivation are defined respectively as:

$$BF_{i,t} = \frac{BUY_{i,t} - FLOW_{i,t}}{TNA_{i,t-1}} \tag{3}$$

$$SF_{i,t} = \frac{SELL_{i,t} + FLOW_{i,t}}{TNA_{i,t-1}} \tag{4}$$

where $FLOW_{i,t}$ is the estimated net investor flow into/out of fund *i* during quarter t, and $TNA_{i,t-1}$ is fund *i* total net assets under management at the end of quarter *t-1*. This paper follows Alexander *et al* (2007) in dividing the time series of portfolios of each fund's holdings that existed during the sample period into five quintiles. The $BF_{i,t}$ metric assigns buy portfolios of funds with high total buy dollar volume and high investor outflows to the top quintile, *BF1*, and buy portfolios with low total buy dollar volume and high investor inflow to the bottom quintile, *BF5*. This ranking procedure, according to Alexander *et al* (2007), deals appropriately with possible serial and cross-sectional trading patterns and correlations that might be present in the holdings data and therefore could bias results in unexpected ways.

BF1 refers to cases where despite a need to raise cash to meet investors outflows, mutual funds will only purchase stocks that are strongly believed to be undervalued, which infers that a large proportion of the buys in these buy portfolios are likely to be motivated by valuation considerations. On the other hand, *BF5* refers to those cases where mutual fund managers might be forced to invest the excess cash from large investor inflows into stocks that are not perceived to be undervalued, and therefore a small proportion of buys in these buy portfolios are likely to be valuation motivated. Similarly, $SF_{i,t}$ assigns sell portfolios with high total sell dollar volume with high investor inflows when a large proportion of sells in these sell portfolios are likely to be driven by valuation motivation to the top quintile, *SF1*, and sell portfolios with low total sell dollar volume with high investor outflows when a small proportion of sells in these sell portfolios are likely to be driven by valuation motivation to the bottom quintile, *SF5*

For illustration purposes, consider an example of the two scenario used by Alexander *et al* (2007) where a fund holds total net assets of $100 million at the beginning of two quarterly report dates. During the quarter of the first report, the fund undergoes net outflows of $10 million and purchase $5 million worth of stocks, while during the quarter of the second report, this fund experiences inflows of $15 million and buys $10 million worth of stocks. The $BF_{i,t}$ metric assigns the higher score of 0.15 = [5 - (-10)] / 100 to buy portfolios for the first report that are more likely to have a larger proportion of valuation-motivated trades, while it assigns a lower score of -0.05 = (10 - 15) / 100 for the second report which has a larger proportions of liquidity-motivated trades. Symmetrical intuition also applies to the $SF_{i,t}$ metric.

3.3.5 Measuring Active Style Drift

The characteristic-timing measure is designed to see whether, and by how much mutual fund managers are able to generate additional performance by increasing (or decreasing) portfolio weights on stock characteristics along the dimensions of size, book to market, and momentum when trading strategies focused on these stock characteristics are most profitable (or unprofitable). However, the characteristic-timing measure is not able to reflect how and to what extent mutual fund managers adjust their portfolio weights across these three different characteristics. In particular, characteristic-timing performance can be generated from passively holding the same stocks in portfolios over time because of fund managers' preference for certain overall stock characteristics, or from active engagement in chasing stock characteristics when they become profitable, or even from aggressive style drift from one equity style category to another one.

In order to investigate the relationship between style drift and characteristic-timing performance, this chapter employs the non-parametric measure developed by Wermers (2012) which allows us to identify the style characteristics of each stock held by mutual funds over time and to track the difference in overall stock style, in each of the three dimensions of size, book-to-market and momentum, in mutual fund portfolio holdings between two periods.

The total style drift of a managed portfolio in style dimension *l* (where *l* = size, book-to-market, or momentum) at portfolio reporting date is measured as:

$$TSD_q^l = \sum_{j=1}^{N} \left(\widetilde{w}_{j,q} \tilde{C}_{j,q}^l - \widetilde{w}_{j,q-1} \tilde{C}_{j,q-1}^l \right) \tag{5}$$

where $\widetilde{\omega}_{j,q}$ is the portfolio weight on stock j at the end of quarter q and $\widetilde{\omega}_{j,q-1}$ is the portfolio weight on stock j at the end of quarter *q-1*, while $\tilde{C}_{j,q}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter q and $\tilde{C}_{j,q-1}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter *q-1*.

The total style drift can be further decomposed into active style drift that results from active changes in the portfolio through trades of stocks, and passive style drift that results from passively holding stocks with changing holding weights and stock characteristics:

$$\mathrm{TSD}_q^l = PSD_q^l + ASD_q^l \tag{6}$$

where PSD_q^l measures the change in style dimension *l* assuming that the manager passively hold the portfolio during quarter *q-1* to quarter q while ASD_q^l measures the change in style dimension *l* through buys and sales of stocks during quarter *q-1* to quarter *q*.

PSD_q^l or passive style drift in dimension *l* during quarter *q-1* to quarter *q* is measured as:

$$PSD_q^l = \sum_{j=1}^{N} \left(\widetilde{w}'_{j,q} \tilde{C}_{j,q}^l - \widetilde{w}'_{j,q-1} \tilde{C}_{j,q-1}^l \right) \tag{7}$$

where $\widetilde{w}'_{j,q}$ denotes the portfolio weight of stock j of quarter q when a manager buys and holds the entire portfolio during quarter *q-1* to quarter *q*, while $\tilde{C}_{j,q}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter q and $\tilde{C}_{j,q-1}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter *q-1*.

The remainder of total style drift is captured by ASD_q^l or the active style drift:

$$ASD_q^l = \sum_{j=1}^{N} \left(\widetilde{w}_{j,q} \tilde{C}_{j,q}^l - \widetilde{w}'_{j,q} \tilde{C}_{j,q}^l \right) \tag{8}$$

Where $\widetilde{\omega}_{j,q}$ is the portfolio weight on stock *j* at the end of quarter *q* while $\widetilde{w}'_{j,q}$ denotes the portfolio weight of stock *j* at the end of quarter *q* when a manager buys and holds the entire portfolio during quarter *q-1* to quarter *q* and $\tilde{C}_{j,q}^l$ equals the non-parametric style characteristic of stock *j* in style dimension *l* at the end of quarter *q*.

Total, passive and active style drifts are then aggregated across all three dimensions of size, book-to-market and momentum effects for a fund during the period between quarter *q-1* to quarter *q* as:

$$TSD_q = \left| TSD_q^{size} \right| + \left| TSD_q^{btm} \right| + \left| TSD_q^{mom} \right| \tag{9}$$

$$PSD_q = |PSD_q^{size}| + |PSD_q^{btm}| + |PSD_q^{mom}| \quad (10)$$

$$ASD_q = |ASD_q^{size}| + |ASD_q^{btm}| + |ASD_q^{mom}| \quad (11)$$

A non-zero value of active style drift would primarily occur due to active changes in portfolio weights of stocks through buys and sells. For example, in the style dimension of book-to-market, a fund manager who believes that the book-to-market effect would be unusually strong for the following month could allocate a higher portfolio weight to high book-to-market stocks by purchasing high book-to-market stocks or selling low book-to-market stocks in his portfolios.

3.4 Data and Sample

My sample uses several data sets. I begin with the Center for Research on Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database. 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 fee including annual expense ratio and management fee, turnover ratio, investment objectives, first offer date and other fund characteristics for each share class of every U.S. open-end mutual fund. The CRSP Mutual Fund Database also provides information on reported portfolio holdings of mutual funds since September 2003, including the identification of portfolios (crsp_portno), holdings report date (report_dt), the effectiveness date of the report (eff_dt), stocks identification code (permno), number of shares held in the portfolio (nbr_shares), and market value of the stocks held (market_val). Holdings data are collected both from reports filed with the SEC and from voluntary reports generated by the mutual funds themselves. The CRSP mutual fund characteristic/returns dataset for each share class of every common mutual fund is linked to the holdings dataset of mutual fund portfolios by using the map (portnomap) provided by the CRSP mutual fund database. The map dataset contains information on the identification of individual share classes (crsp_fundno) and their common funds (crsp_portno) over time, as well as other share class characteristics including delist date, delist type, and the identification of the acquirer share classes and the latest available date for monthly net assets value for the target share classes.

Following the literature on mutual fund performance, the focus of my analysis is on the actively managed U.S. domestic equity mutual funds for which the holdings data are most complete and reliable and therefore, this paper eliminates balanced, bond, money market, international, sector, index, ETF, exchange target, and target date funds as well as those funds not invested primarily in equity securities. This screening procedure generates a sample of 109054 fund-report observations with a total of 3384 unique U.S. domestic equity mutual fund samples from September 2003 to December 2013. Summary statistics relating to my sample of funds are presented in Table 3.1.

I use the CRSP/Compustat stock-level database, which provides data on stock identification, stock return, delisting return, share price, trading volume, cumulative price adjustment factors, cumulative shares adjustment factors, and shares outstanding as well as other stock characteristics. To estimate stock equity value using the approach of Daniel and Titman (1997), I also obtain shareholders' equity (SEQ), deferred taxes (TXDB), investment tax credit (ITCB), and preferred stock (PREF).

3.5 Empirical Findings

3.5.1 Fund Behaviours in Response to Investor Flows

The structure of open-end mutual funds forces fund managers to trade in response to fund flows. First, an important role of open-end mutual funds is to provide liquidity to investors. Fund managers are required by law to pay a proportional share of the net asset value of the fund to each investor who chooses to redeem their investment. Second, since fund managers' compensation depends on their ability to track and beat their benchmark portfolios (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998), they have strong incentives to trade to counteract flow shocks so that they can maintain the efficient fraction of equity investment in their portfolios.

To investigate the trading behaviours of mutual funds in response to investor flows, this chapter divides mutual funds into quintiles according to their net realised flows. Table 3.2 summarises mutual fund trading and style drift behaviours in response to investor flows. Panel A reports average past fund performance, cash holdings and numbers of stocks in portfolios by flow quintiles. Panel B and Panel C present fund trading behaviours in response to realised fund flows. In particular, Panel B takes the fraction of a given fund's position that is initiated, expanded, reduced, or eliminated during the given quarter and average these value across mutual funds within each flow quintile. Panel C reports the absolute changes in fund portfolio's style quintile number along the three stock characteristics of size, book-to-market, and momentum through buying and selling (i.e., active style drift).

A variety of interesting patterns emerge from Panel A in Table 3.2. First, mutual funds experience a wide range of quarterly flows. Funds in the top quintile experience an average outflow of -9.26% while funds in the bottom quintile experience inflows of 14.7%. Second, funds that experience heavy outflows had only average past returns of 5.5% while those that attract heavy inflows exhibited past returns of 12.17%. This is consistent with the finding in the literature, namely that in general well performing mutual funds are rewarded by investor inflows while poorly performing mutual funds are penalised to experience investor redemptions. Third, mutual funds in the bottom quintile (heavy inflows) hold 50% more cash (4.05% vs. 2.61%) than those in the top quintile (heavy outflows), which is consistent with the notion that these funds will have more flexibility in their trading. Surprisingly, the final column in Panel A indicates that mutual funds that experience significant flows appear to be less diversified than funds with more moderate flows in terms of number of stocks held in their portfolios. In particular, mutual funds experiencing heavy inflows (outflows) hold a total of 104.40 (110.88) stocks in their portfolios while mutual funds experiencing median flows hold a total of 120.12 stocks.

Panel B presents fundamental evidence on the response of fund managers to fund flows. Consistent with the expectation that mutual funds experiencing significant outflows have no choice but have to sell some of their holdings to meet redemption requirements, mutual funds in the top quintile (heavy outflow) are far more likely to reduce or eliminate current positions than funds experiencing inflows. On average, these funds reduce or eliminate 52% of their existing positions, whereas mutual funds in the bottom quintile only reduce or eliminate 20% of its existing positions. Perhaps, more interestingly, mutual funds experiencing inflows are more likely than other funds to expand their existing positions. For instance, funds in the bottom quintile increase 44% of their existing holdings which is more than triple the rate for funds that are not experiencing inflows. It is also surprising that mutual funds that experience extreme investor flows are more likely to initiate new positions and eliminate existing positions, compared to funds with moderate flows.

Panel C shows that on average, mutual funds experiencing extreme outflows (inflows) actively drift a total of 0.25 (0.21) quintile units in the three stock characteristics of their portfolios through trading. Specifically, managers in the top quintile who experience heavy outflows move 0.06 quintile units in their size characteristic, 0.09 in book-to-market, and 0.10 in momentum, while managers in the bottom quintile who experience heavy inflows move 0.05 quintile units in their size characteristic, 0.07 in book-to-market, and 0.09 in momentum. These results indicates that mutual fund managers are far more likely to engage into active style drift across all three stock characteristics when they are experiencing extreme investor flows.

Overall, my results show that fund managers who experience significant outflows appear to be much more likely to reduce or eliminate their existing holdings, whereas those who receive substantial fund inflows are far more likely to expand their existing holdings. Moreover, both groups of fund managers engage in large active style drifts. These findings suggest that fund flows can be highly influential in shaping fund managers' trading decisions and that an adjustment in the fund performance measure to account for the potentially adverse effect of fund flows is important to achieve an unbiased, or at least less biased assessment of fund manager skills.

3.5.2 Do Investor Flows Act as Drag of Characteristic-Timing Performance?

Given the abnormal trading behaviours in response to fund flows observed in Table 3.2, one might naturally ask whether, and to what extent, fund flows affect fund performance. In the context of timing performance, consider a mutual fund manager who initially holds some target efficient portfolio in terms of level of risk exposure toward the three stock characteristics. Unanticipated fund flows would then force this fund manager make trades that could his fund portfolio to shift away from his initial efficient target portfolio. When experiencing fund outflows, fund managers often have to sell some of their existing holdings to fulfil investor redemption requirements. In extreme cases, they can also be forced to engage in fire sales (Coval and Stafford, 2007). These liquidity-driven sales can move fund portfolios away from fund managers' intended exposure to style factors because fund managers might need to sell down their liquid positions to avoid a high liquidity premium. On the other hand, despite the need to maintain an efficient fraction of equity investment in their portfolios, fund managers who have fund inflows have more flexibility in their trading: they can accumulate cash for cash redemption needs; they can postpone their equity investment decisions; and they can immediately open new positions or expand their current holdings. If fund managers can take advantage of the financial flexibility provided by investor flows, one should observe better, at least not worse performance by those fund managers with fund inflows compared with those who experience significant outflows.

In contrast with expectations, Table 3.3 shows that mutual fund managers who experience heavy investor inflows (*NF5*) exhibit statistically and economically significant characteristic-timing returns of -0.85% per year (t-statistic=-2.86), while those who have heavy investor outflows exhibit no characteristic-timing performance. The difference in characteristic-timing performance between *NF1* and *NF5* is significantly positive 0.78% per year (t-statistic=2.80) with this difference driven by the underperformance of mutual funds that experiencing heavy inflows. Moreover, no mutual fund investment objective subgroups exhibits any characteristic-timing performance when experiencing heavy outflows while all subgroups exhibit negative characteristic-timing performance when facing heavy inflows. In particular, income mutual funds appear to have the worst performance when they face extreme investor inflows.

In a further refinement, mutual fund portfolios within each flow quintile are sorted and categorised into another 5 quintile groups based on their active style drift at the end of each quarter. *SD1* refers to portfolios which engage in large active style drift and *SD5* refers to the portfolios which engage in small style drift. The rationale is that when facing investor flows, fund managers could simply proportionally adjust current holdings to minimise the impact of inflow shock to portfolio risk exposure and control liquidity. They will engage in active style drift along the three stock characteristics by buying (selling) stocks, when and only when they strongly believe that these stocks will have good (poor) future characteristic-timing performance. In other words, managers who strongly believe that certain stock characteristics would have superior future performance will make active style changes moving their portfolio equity style factors from one category to another over the quarter. But managers who need to control for liquidity will make smaller adjustments across the three characteristics. If this is the case, one should observe that the portfolios with high level of active style drift when experiencing heavy unanticipated flows have better subsequent characteristic-timing performance. However, if these style bets are motivated by reasons other than valuation beliefs, a negative relationship should be observed.

Table 3.4 reports aggregate characteristic-timing performance results for mutual fund portfolios categorized by active style drift and concurrent investor flows. The first three rows and three columns of each panel report results from two way sorting on net investor flows and active style drift. The fourth row and fourth column present results from one-way sorting only on active style drift and net investor flows, respectively. The fifth row and fifth column report the difference between the extreme investor flow and active style drift quintiles.

Consider now the upper left-hand corner of Panel A where we find *NF1/SD1* (i.e., large active style drift concurrent with heavy outflows), the fund portfolios that should reflect managers' strong beliefs about the future performance of certain stock characteristics. Inconsistent with the expectation, *NF1/SD1* exhibits a negative but marginally significant -0.92% characteristic-timing return per year. Similarly, as we move down to *NF5/SD1* (i.e., large active style drift concurrent with heavy inflows), reflecting the large style bets of mutual fund managers when they have financial flexibility. These portfolios are associated with economically and statistically significant characteristic-timing returns of -1.76% per year (t-statistics=-2.78). These results therefore provide evidence for the competing hypothesis that active timing decisions might be motivated by reasons other than valuation beliefs, such as overconfidence.

Small style drifts could be simply motivated by the need to control liquidity. When fund managers face heavy outflows, they could proportionally reduce their existing holdings to raise cash. These sales are more likely to be driven by liquidity needs, and thus are less likely to reflect managers' valuation beliefs. Consistent with my expectation, *NF1/SD5* (i.e., small active style drift concurrent with heavy outflows) shows a statistically and economically insignificant -0.02% characteristic-timing return per year. Similarly, fund managers could proportionally expand their holdings when experiencing significant inflows. *NF5/SD5* (i.e., small active style drift concurrent with heavy inflows) exhibits a negative statistically significant -0.90% characteristic-timing return per year. I interpret these results as consistent with no significant characteristic-timing ability.

To summarise, this chapter shows that fund flows have an adverse effect on fund characteristic-timing performance. By conditioning portfolios on the direction and magnitude of fund flows, mutual fund managers appear to exhibit significantly negative characteristic-timing performance only when they experience significant fund inflows. Inconsistent with Simutin (2014) who argue that financial flexibility allows fund managers to satisfy redemption requests and capture investment opportunities quickly, my results suggest that fund managers seem to be not able to take advantages of the financial flexibility provided by fund inflows. Instead, excessive cash holdings from fund inflows impose a significant drag on characteristic-timing performance. This argument is confirmed by the results of further investigation conditioning portfolios based on the magnitude of active style drifts as a proxy for fund manager conviction. Large style bets that should reflect the strong valuation beliefs when managers have excess cash from investor flows are associated with significantly negative characteristic-timing returns. Overall, this chapter extends the insight of Edelen (1999) and provides evidence that the "perverse" timing ability is not entirely driven by the adverse effect of fund flows, but at least partly due to fund managers' negative timing ability. Furthermore, these surprising results are consistent with the free cash flows hypothesis that is well documented in the corporate finance literature. Free cash flow hypothesis suggests that firms' managers tend to use free cash flows to finance low-return projects (e.g., Jensen, 1986).

3.5.3 Does Trade Motivation Relate to Characteristic-Timing Performance?

3.5.3.1 Conditioning on Motivation Score

Chen *et al* (2013) document that mutual fund managers exhibit distinct trading skills by decomposing their aggregate characteristic-timing performance into buying and selling components. Their study, however, gives no consideration to the fact that fund managers provide a great deal of liquidity to investors and that this provision of liquidity forces fund managers to engage in costly trading. Thus, the inference regarding fund manager trading skills in their study can be significantly negatively biased. One might naturally ask whether negative characteristic-timing performance when selling stocks is driven by liquidity-induced sales. This sub-section attempts to address this question.

To increase the test power of the standard characteristic-timing performance measure, I separate fund managers' motivations for trading by conditioning fund purchases and sales on the motivation score metrics of Alexander *et al* (2007). Intuitively, the flow-based motivation score metric assigns a higher score to buy (sell) portfolios of funds that are more likely comprised of larger proportions of valuation motivated purchases (sales). This approach has several advantages over realised net fund flows. First, motivation score metrics not only consider realised net investor flows between two quarters, but also capture total trading volume from buying and selling actives during the corresponding period. Second, the ranking procedure based on motivation score breaks down possible serial and cross-sectional trading patterns and correlations that might be present in the stock holdings data and therefore could bias results in unexpected ways (Alexander *et al*, 2007).

Panel A of Table 3.5 provides evidence that buying characteristic-timing ability is strongly related to trade motivations. Consistent with the expectation that mutual fund managers (All Funds) possess positive buying skill, in the case of *BF1* (i.e., large total purchase volume concurrent with heavy outflows), buy portfolios that have the highest proportion of valuation-motivated buys show a statistically and economically significant characteristic-timing return of 1.90% per year higher than the average across the three different characteristic styles. When moving down the rows from *BF1*, one can observe generally decreasing returns because buy portfolios are characterized by a decreasing proportion of valuation-motivated buys and an increasing proportion of liquidity-induced buys. In particular, in the case of *BF5* (i.e., low total purchase volume concurrent with heavy inflows), buy portfolios that consist of the highest proportion of liquidity-driven buys exhibit no statistically significant characteristics-timing returns. As expected, valuation-motivated buys outperform liquidity-driven buys (*BF1-BF5*) by an average of 0.93% per year, statistically significant at the 1% level. While this pattern holds for all investment categories, there is some evidence to show that income oriented mutual funds appear to have lower characteristic-timing returns from their valuation-motivated purchases.

In Panel B, the results for sell portfolios are organised in the same ways as for the buy portfolios. Consistent with mutual fund managers (All Funds) having negative selling skill, *SF1* (i.e., high total stock sales concurrent with high inflows), sell portfolios that have the highest proportion of valuation-motivated sales have a statistically and economically significant characteristic-timing return of -1.57% per year. On the other hand, in the case of *SF5* (i.e., low total stock sales concurrent with high outflows), the sell portfolios that have the highest proportion of liquidity-driven sales show an average characteristic-timing returns of -2.24% per year, significant at the 5% level. The difference between valuation-motivated sales and liquidity-driven sales (*SF1-SF5*) is statistically and economically significant at 0.69% per year. This suggests that despite lacking selling ability in general, trade motivation still matters in terms of subsequent characteristic-timing performance. The remaining columns in Panel B demonstrate a similar story, namely that none of the investment categories exhibits positive selling skill and that valuation-motivated sales outperform liquidity-induced sales.

3.5.3.2 Multivariate Regression Evidence

In this section, I further extend my analysis of fund manager trading skills using multivariate regressions. This approach differs from the above portfolio approach in three major respects. First, a multivariate regression framework can simultaneously control for mutual fund characteristics that might be related to trade motivations or/and fund manager trading performance. Second, fund managers might be motivated to trade due to other reasons, such as for tax management and window-dressing purpose. According to the mutual fund tournament literature, these trades typically occur before the fiscal year end. Regression analysis can effectively control these effects by introducing year-end dummy variables. Third, the portfolio approach aggregates mutual funds of similar trade motivation scores into quintile groups, while the regression approach allows researchers to take advantage of the rich panel structure to directly look at individual mutual funds.

I begin with sorting fund-month observations for each fund based on motivation scores for purchase (*BF*) and divide these observations into high, mid and low motivation score subgroups. An indicator variable, $Valuation_t^i$, is constructed to capture the purchases that are the most likely to be motivated by valuation beliefs, and the other dummy variable $Liquidity_t^i$ is used to identify liquidity-induced purchases. This procedure is repeated for selling skills. I test the hypothesis that trade motivations are related to subsequent characteristic-timing performance by estimating the following fixed effect panel data regression model separately for buying and selling skills:

$$Ability_t^i = a_0 + a_1 Valuation_{t-1}^i + a_2 Liquidity_{t-1}^i + a_3 Control_{t-1}^i + \epsilon_t^i$$

where $Ability$ denotes either $Selling$ or $Buying$; $Valuation_{t-1}^i$ is an indicator variable equal to one if the mutual fund *i* is categorised as being more likely to be motivated by valuation beliefs at time *t-1*, and zero otherwise; $Liquidity_{t-1}^i$ is an indicator variable equal to one if the mutual fund *i* is categorised as being more likely to be motivated by liquidity needs at time *t-1*, and zero otherwise. $Control_{t-1}^i$ is mainly a vector of lagged fund-specific control variables, including age (natural logarithm of age in years since first offer date, *log(AGE)*), size (natural logarithm of total net assets under management in millions of dollars, *log(TNA)*), expense ratio (in percent per year, *Expenses*), turnover rate (in percentage per year, *Turnover*), percentage flow (the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to

$TNA_{i,t-1}$, *Flow*), management fee (in percentage per year, *Fee*) and fund style characteristics along the size, book-to-market and momentum dimensions (in quintile number, *size*, *btm*, and *momentum*). To mitigate the impact of outliers on my estimates, I winsorize *Flow* and *Turnover* at the 1% level. I demean all these control variables so that the constant a_0 measures the performance of trades when fund managers are "normally" motivated, and a_1 indicates how much skills increase when fund managers are motivated by valuation beliefs, while a_2 indicates how much skills decrease when fund managers are motivated by liquidity needs. In addition to these control variables mainly from Kacperczyk *et al* (2014), I also include two variables to control the effect of the financial crisis (defined by the NBER, *Recession*) and the fourth calendar quarter (*4th Quarter*). The latter is motivated by Alexander *et al* (2007) and others working in tournament literature who argue that there is the possibility that some trades may be motivated by tax management or window-dressing reasons which typically occur just before the fund's fiscal year end.

Table 3.6 examines the variation in buying and selling skills based on trade motivations. Column (1) to Column (3) show the coefficients on trade motivation from the panel regression using the characteristic-timing returns of buy portfolios as the dependent variable. The sign and magnitude of the coefficients on both motivation indicator variables are consistent with the previous analysis based on the trade motivation quintile portfolios across all three model specifications. For example, in Column (3), valuation-motivated purchases are associated with 7 basis points per month or approximately 0.85% per year higher returns than others purchases while liquidity-driven purchases are associated with 4.7 basis points per month or 0.56% per year lower returns than others purchases, after controlling for fund-specific characteristics and time fixed effects. The effects of trade motivation on subsequent performance are economically and statistically significant. Likewise, Column (4) to Column (6) reports that valuation-motivated sales outperform other sales by an average of 4.3 basis points per month or 0.52% per year, while liquidity-induced sales substantially underperform other sales by a statistically and economically significant 12 basis points per month or about 1.43% per year. Again, signs and magnitudes of the coefficients are consistent with previous portfolio analysis.

3.5.3.3 Conditioning on Motivation Score and Trade Size

Another test of managers' timing ability is attainable by studying their individual stock trades. Trades within each motivation score categorized portfolio are further split into another 5 quintile groups on the basis of their dollar volume. Alexander *et al* (2007) argue that large trades are more likely to be driven by valuation motivation, whereas small trades are more likely to be liquidity motivated. The rationale is that fund managers would want to buy a relatively large amount of stocks that they believe are undervalued, but they are more likely to make smaller-size purchases when dealing excess liquidity from unanticipated investor inflows. Similarly, fund managers would want to sell a relative large amount of stocks when they no longer believe that these stocks are attractive while they might spread the smaller-size sales across the stocks in their the portfolios to meet investor redemption requests.

Panel A of Table 3.7 summarizes characteristic-timing performance for buy portfolios categorized by net investor flows and trade size. Stocks mutual fund managers purchase in the *BF1/TS1* group (i.e., large buys concurrent heavy outflows) are associated with subsequent significantly positive characteristic-timing returns of 1.61% per year. Moving down the rows from *BF1* to *BF5* and across the columns from *TS1* to *TS5*, generally decreasing trends of characteristic-timing returns are reported as these portfolios are characterised by a decreasing proportion of valuation-motivated, but an increased percentage of liquidity-motivated buys. Difference of characteristic-timing performance between large buys (*TS1*) and small buys (*TS5*) is 1.45% per year in the group where buys are most likely valuation-motivated. This difference goes down to 0.58% per year in the group of lowest valuation-motivated buys. A similar pattern holds when the difference in characteristic-timing performance between valuation-motivated buys and liquidity-motivated buys is conditional on trade size. The difference between the two extreme groups: *BF1/TS1*, which contain the highest proportion of valuation-buys, and *BF5/TS5*, which have the highest proportion of liquidity-motivated buys, is statistically and economically significant with characteristic-timing returns of 1.56% per year. These results are consistent with previous findings that fund managers possess positive buying skill, and that valuation-based purchases outperform liquidity-driven purchases.

Panel B presents the subsequent characteristic-timing returns of fund managers' sells, which are categorized by the *SF* metric and trade size. Characteristic-timing performance for selling in the category *SF1/TS1* (i.e., large sells and high total sales concurrent with heavy inflows) is statistically significant but negative or -0.87% per year. There is a decreasing trend in characteristic-timing performance for sell portfolios characterised by the decreasing proportions of valuation-motivated sells and increasing proportions of liquidity motivated sells from *SF1* to *SF5*. Difference between the category *SF1/TS1* and *SF5/TS1* is significantly positive or 1.91% per year, indicating that even though mutual fund managers have negative characteristic-timing selling ability, trade motivation still matters.

However, when moving across columns from large sells (*TS1*) to small sells (*TS5*), an increasing trend of characteristic-timing performance is observed, which is inconsistent with the expectation that large sells that are more likely to be motivated by valuation beliefs should outperform small sells. Instead, within any net investor flow category from *SF1* to *SF5,* large sells tend to underperform small sells in terms of subsequent characteristic-timing returns. When experiencing heavy investor outflows, mutual fund managers appear to exhibit significantly negative characteristic-timing returns of -2.73% per year from large sells (*SF5/TS1*), while insignificant but positive characteristic-timing performance of 0.03% per year from small sells (*SF5/TS5*). The difference between these two groups is statistically and economically significant. I interpret this finding as consistent with the notion that mutual fund managers have negative timing ability when selling stocks. Large bets when selling stocks might be more likely to reflect other reasons than valuation beliefs, such as behavioural bias.

Overall, by segmenting trades based on the motivation for making them, I find evidence that trade motivations are strongly related to subsequent trade performance. In particular, valuation-motivated trades significantly outperform liquidity-induced trades, and this pattern holds for both buying and selling dimensions. However, fund managers appear to exhibit negative selling ability even when they are highly motivated by valuation beliefs, which directly supports and extends the argument of Chen *et al* (2013) who show that in general mutual fund managers exhibit poor selling characteristic-timing abilities. These findings are robust when using a multivariate regression approach to control for fund characteristics and time fixed effects.

3.5.4 Are there managers who possess both good buying and good selling skills?

Findings reported thus far show that mutual fund managers on average possess apparent buying skill but exhibit negative selling skill which is consistent with Chen *et al* (2013). By conditioning on trade motivations, further evidence does not improve this unfavourable finding regarding selling ability. Instead, valuation-based sales are associated with significantly negative subsequent characteristic-timing returns, indicating that on average fund managers exhibit negative selling skill even when these sales are motivated by valuation beliefs. However, such underperformance in general does not necessarily mean that no mutual fund managers possess good selling skills. Most studies in the literature on mutual fund performance treat fund managers as a homogeneous class of professional investor, and have not yet explored whether one group of fund managers is better at buying and another group of fund managers specialise in selling, or that a small subset of managers can perform both buying and selling well.

To examine whether different groups of fund managers possess different skills, I begin by testing the prediction that the same mutual funds that exhibit good selling skills display good buying skills. Since valuation-motivated trades are more likely to reflect the true trading skills of fund managers, I first identify "good sellers", those mutual funds with superior selling ability when they are most likely to be motivated by valuation beliefs. To achieve this, for each fund, I divide all fund-month observations into three subsamples according to motivation scores for selling (*SF*). Within the subsamples of fund-month observations that are mostly likely to have the highest proportion of valuation-motivated sales (high motivation score), I select fund-month observations that are in the highest 25% of the $Selling_t^i$ distribution. Then, an indicator variable Top ($Top_i \in \{0, 1\}$) is formed to identify those managers who have the best record for valuation-motivated selling, which is equal one for the 25% of funds with the highest fraction of observations (months) in that group, relative to the total number of observations for that fund in the high motivation score subsample. Next I estimate the following pooled panel data regression model:

$$Ability_t^i = c_0 + c_1 Top_t^i + c_2 Control_{t-1}^i + \epsilon_t^i$$

Where $Ability$ denotes either $Selling$ or $Buying$, Top denotes either "good sellers" or "good buyers", and $Control$ is a vector of previously defined control variables. The coefficient of interest is c_1.

Table 3.8 summarises the pooled panel data regression estimates with different model specifications. Column (3) shows that on average "good sellers" are significantly better at characteristic-timing when selling stocks than all other funds, after controlling for fund characteristics and other time effects. The coefficient of the indicator variable Top is statistically and economically significant. This is true given the way "good sellers" are identified. When mutual fund managers are highly motivated by valuation beliefs, $Selling$ is 11.2 basis points per months or 1.35% higher for "good sellers" than for the remaining funds. The main point of Table 3.8 is that the same "good sellers" are on average also better at $Buying$ when they are motivated by valuation beliefs. Column (6) presents the positive coefficient on the indicator variable Top, which is statistically significant at the 1% level. The effect is also economically meaningful. $Buying$ is 7.2 basis points per month or 0.87% per year higher for the same "good sellers" than for all other funds. In sum, these results suggest that there are a small number of mutual fund managers who possess selling skill and also exhibit positive buying skill.

I repeat the above analysis procedure for "good buyers" who are the funds in the top 25% of the buying skill distribution. In Table 3.9, Column (3) shows that on average "good buyers" are significantly better at buying stocks than all other funds, after controlling for fund characteristics and other time effects, which follows the construction of the "good buyer" set of funds. These successful buyers exhibit 30.7

basis points per month or 3.75% per year higher characteristic-timing performance when buying stocks based on valuation beliefs. Strikingly, these "good buyers" are not able to outperform the other funds when selling stocks. This result is evident from the negative but statistically insignificant coefficient on Top in column (6). Overall, it is very interesting to see that "good sellers" who by construction are good at selling ability also possess good buying ability, while "good buyers" who by construction are significantly successful at characteristic-timing when buying stocks are not able to outperform all other funds when selling stocks. In other words, "good sellers" are also "good buyers" but "good buyers" are not "good sellers".

If the same "good sellers" are able to time stock characteristics well when buying and selling stocks in their portfolios, then these fund managers should also outperform unskilled funds in terms of aggregate characteristic-timing, whereas "good buyers" who are good at buying but are not capable of selling might not be able to exhibit superior aggregate characteristic-timing ability. To investigate this, I estimate the above pooled panel data regression with aggregate characteristic-timing performance as dependent variables for "good sellers" and "good buyers" separately. Consistent with expectation, Column (3) of Table 3.10 shows that aggregate characteristic-timing performance is 2.6 basis points per month or 31.2 basis points per year higher for "good sellers" than all other funds, which is statistically significant at the 1% level after controlling for fund characteristics and time effects. Column (6) shows that the coefficient of Top for "good buyers" is economically and statistically insignificant, indicating that on average "good buyers" exhibit no aggregate characteristic-timing ability. These results indicate that there are a small number of mutual fund managers that possess timing abilities, and the superior characteristic-timing performance is mainly attributed to their selling skills.

These findings are robust to changing the cut-off levels for inclusion in the Top portfolio and using an alternative way to identify "good sellers" or "good buyers" by conditioning on trade motivation based on net investor flows. The main findings that good sellers are also good buyers but good buyers are not necessarily good seller and that good sellers possess superior aggregate characteristic-timing ability hold.

To summarise, I find strong evidence to suggest that there are a small number of mutual funds in my sample that possess both good buying and selling skills in timing stock characteristics along the size, book-to-market, and momentum dimensions. By estimating panel data regressions of characteristic-timing performance on the indicator variable for "good sellers", my results reveal that "good sellers", namely mutual fund managers who by construction have the best performance record for selling, also have superior characteristic-timing performance when buying stocks compared with all other funds, after controlling for fund characteristics and time effects. However, there is no evidence to show that "good buyers" who by construction are good at buying exhibit superior characteristic-timing performance when selling stocks than all other funds. Furthermore, "good sellers" exhibit superior aggregate characteristic-timing performance, while "good buyers" do not have outperformance. I interpret this as being consistent with the behavioural finance literature which shows that sell decisions are particularly difficult because they are more likely to be susceptible to behavioural biases and heuristics, even for mutual fund managers who are skilled at buying. Fund managers who are good at the difficult task of selling stocks perhaps possess genuine investment talents so that not only do they outperform other funds when buying stocks, but they also exhibit superior aggregate characteristic-timing performance.

3.5.5 The Characteristics of Good Sellers

Table 3.11 summarises the fund characteristics of "good sellers" in comparison with the remaining funds. Several interesting differences emerge. First, "good sellers" are younger than other fund managers in my sample. Second, they have less assets under management, suggestive decreasing returns to scale at the fund level (e.g., Berk and Green, 2004). Third, "good sellers" appear to charge higher expenses and management fees to fund investors, perhaps reflecting higher rents to their customers for their superior skills. Fourth, they exhibit higher portfolio turnover, indicating that these mutual funds are more active than other funds. Fifth, they tend to hold portfolios with a smaller number of stocks, and therefore, tend to be somehow more concentrated. Finally, they are more likely to actively engage in style drift, suggesting that their superior characteristic-timing performance comes from active style drift along the size, book-to-market, momentum dimensions. In sum, in line with previous studies that find there does exist a subset of skilled managers, "good sellers" seem to be younger, manage smaller funds and are more active as measured by turnover ratio, diversification, and active style drift than all other funds, but they also charge higher expenses and management fees to compensate for their superior skills.

3.6 Conclusion

Previous return-based studies on the timing ability of mutual fund managers may be questioned on the basis of the strong assumption made that managers implement timing strategies in a specific way. The documented negative timing ability in these studies can be potentially caused by the "artificial timing" of non-linear option-like returns from managers' dynamic trading strategies. Furthermore, without considering the adverse effect of investor flows, the timing ability of fund managers can be underestimated.

This chapter therefore aims to overcome these estimation issues in most previous studies by evaluating the timing ability of mutual fund managers using the characteristic-timing measure of Daniel *et al* (1997). By segmenting fund portfolios based on net investor flows, my analysis contributes to the literature by revealing that mutual fund managers appear to have significantly negative characteristic-timing performance when and only when they experience investor inflows. In a further refinement, my results show that large style bets, which should reflect the strong valuation beliefs, as measured by active style drift measure of Wermers (2012), are surprisingly associated with significantly negative characteristic-timing returns of -1.76% per year, when managers experience investor inflows. These results suggest that negative characteristic-timing performance is not entirely driven by fund flows but at least partly due to fund managers' poor timing ability.

Existing literature on timing skill of fund managers has concentrated on looking at whether mutual fund managers have timing ability by testing aggregate timing performance, which might not necessarily be a good indicator of the timing skills that mutual fund managers really possess. Chen *et al* (2013) decompose aggregate characteristic-timing skill into buying and selling abilities and find that "star" growth oriented fund managers have good buying skill but bad selling skill. Motivated by Alexander *et al* (2007), this chapter goes further and explores whether trade motivations are related to differential buying and selling performance. By conditioning trades on the motivation for making them, my results shows that valuation-motivated trades are associated with higher subsequent characteristic-timing performance than liquidity-driven trades. Perhaps more interestingly, stocks sold by managers who have excess liquidity following significant investor inflows, which are expected to have a higher proportion of valuation-motivated sales, are on average still associated with statistically significant and negative characteristic-timing returns of -1.57% per year. These results suggest that average managers seem to be unable to generate positive characteristic-timing performance when selling stocks, even when these sales are valuation-motivated. Thus, this chapter finds evidence that strongly supports and reinforces the findings of Chen *et al* (2013), which is restricted to a small number of "star" growth oriented mutual funds.

This chapter further investigates the possibility of whether there is a group of fund managers that specializes in selling, while another group of managers is particularly good at buying, or the same group of managers can perform both tasks well. I find strong evidence that there are a small number of mutual funds in my sample that possesses both good buying and selling skills to time stock characteristics along the size, book-to-market, and momentum dimensions. Results reveal that "good sellers", those fund managers who have the best performance records for selling, also show superior characteristic-timing performance when buying stocks compared with all other funds. However, there is no evidence to show that "good buyers" exhibit any superior characteristic-timing performance when selling stocks over and above all other funds. Furthermore, "good sellers" exhibit significant aggregate characteristic-timing performance, while "good buyers" do not outperform other funds in aggregate. Comparing fund specific characteristics with other funds, "good sellers" appear to be younger, smaller and more active in managing their portfolios in terms of turnover ratio, diversification, and active style drift than all other funds, but they also tend to charger higher expenses and management fees to compensate for their superior skills.

Table 3.1 Summary Statistics of Mutual Fund Samples

The table below reports the summary statistics of a total of 3384 unique U.S. domestic equity mutual fund samples from September 2004 to December 2013. 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 U.S. Database. CRSP investment objective variable (crsp_obj_cd) is used to filter U.S. 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. Total number of funds is the total number of unique mutual funds that exist during the sample periods. Avg number of stocks is the times series average of cross-sectional average of the number of unique stocks held by mutual funds during the sample periods. Avg TNA is times series average of cross-sectional average of total net assets under management of mutual funds. Avg Flow is time series average of cross-sectional average of estimated percentage change in TNA adjusted for investment return and mutual fund mergers. Avg Turnover is time series average of cross-sectional average of mutual fund turnover ratio. Avg Exp is time series average of cross-sectional average expense ratio of mutual fund. 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.

	Total Number of Funds	**Avg Number of Stocks**	**Avg TNA (in $ Million)**	**Median TNA (in $ Million)**	**Avg Flow (%/Month)**	**Avg Turnover (%/Year)**	**Avg Exp Ratio (%/Year)**
Panel A: Summary statistics of all mutual fund samples over time							
2004	1360	126.94	$1,327.63	$178.00	7.24	89.54	1.34
2005	1459	120.09	$1,354.98	$197.80	5.56	86.17	1.29
2006	1479	112.61	$1,512.18	$224.40	3.95	86.13	1.28
2007	1638	114.71	$1,483.71	$202.20	2.63	91.09	1.25
2008	2046	115.75	$821.48	$124.40	0.31	88.76	1.19
2009	2022	122.04	$1,059.28	$162.75	1.89	100.46	1.20
2010	2727	109.65	$1,097.55	$210.40	3.05	90.41	1.18
2011	2612	103.05	$1,011.80	$201.85	1.57	83.66	1.16
2012	2577	117.82	$1,105.19	$218.70	1.19	79.77	1.12
2013	2454	120.80	$1,502.37	$321.85	7.29	72.94	1.10
Panel B: summary statistics of mutual fund with different investment objectives							
All	3384	115.90	$1,217.94	$205.20	7.25	87.19	1.22
Growth	1529	100.48	$1,933.87	$254.50	10.89	92.59	1.22
Growth&Income	576	103.45	$1,332.02	$181.00	4.68	71.76	1.11
Income	191	78.90	$1,508.81	$317.60	14.48	48.60	1.09
Micro-Cap	50	111.93	$187.91	$101.65	2.71	92.92	1.66
Small-Cap	679	170.93	$843.47	$233.75	1.55	89.91	1.29
Mid-Cap	470	113.35	$728.33	$201.60	5.99	97.00	1.24

Table 3.2 Mutual Fund Behaviors in Response to Investor Flows

This table reports how quarterly mutual fund holdings changes conditional on actual investor flows. *Net flow* is estimated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. Panel A reports the net flow, prior 12-month fund returns, cash holdings and number of stocks held by mutual funds averaged across all funds in the decile. Panel B reports for the average fund the fraction of positions that were initiated, expanded, reduced and eliminated. Panel C reports the active style drift from Wermers (2012) calculated as the changes in quintile number along size, book-to-market, and momentum dimensions.

Net flow quintiles	**Net flow**	**Prior fund return**	**Average cash/tna**	**Avg number of stocks**
Panel A				
1	-9.29%	5.50%	2.61%	110.88
2	-2.38%	8.00%	2.47%	113.55
3	-0.08%	11.09%	2.39%	120.12
4	0.69%	11.84%	2.89%	118.85
5	14.70%	12.17%	4.05%	104.40
Net flow quintiles	**Initiated**	**Expanded**	**Reduced**	**Eliminated**
Panel B				
1	0.14	0.13	0.38	0.14
2	0.09	0.15	0.30	0.09
3	0.06	0.16	0.23	0.06
4	0.07	0.25	0.15	0.07
5	0.11	0.44	0.10	0.10
Net flow quintiles	**Active style drift**	**Active size drift**	**Active btm drift**	**Active momentum drift**
Panel C				
1	0.25	0.06	0.09	0.10
2	0.16	0.03	0.06	0.07
3	0.11	0.02	0.04	0.05
4	0.12	0.03	0.04	0.05
5	0.21	0.05	0.07	0.09

Table 3.3 Aggregate Characteristic-Timing Performance, Conditioning on Net Flows

This table reports the aggregate characteristic-timing performance conditioning on net investor flows. Net investor flows are calculated as estimated percentage change in TNA adjusted for investment return and mutual fund mergers. For each month, mutual funds are divided into five quintiles based on net investor flows. The mutual funds are broken down by the CRSP investment objectives, including growth, growth & income, income, micro-cap, small-cap, and mid-cap. The t-statistics are presented below in parentheses.

	All Funds	Growth	Growth &Income	Income	Micro-Cap	Small-Cap	Mid-Cap
NF1	-0.07%	-0.14%	-0.40%	0.41%	-0.32%	-0.32%	0.43%
	(-0.23)	(-0.36)	(-0.92)	(0.57)	(-0.58)	(-0.94)	(1.16)
NF2	-0.26%	0.09%	-0.93%**	-0.63%	-0.62%	0.17%	-0.13%
	(-1.04)	(0.27)	(-2.05)	(-0.89)	(-1.32)	(0.47)	(-0.31)
NF3	-0.18%	-0.36%	-0.31%	-0.35%	-0.85%	-0.04%	-0.23%
	(-0.59)	(-1.00)	(-0.60)	(-0.63)	(-1.43)	(-0.10)	(-0.52)
NF4	-0.53%	-0.43%	-0.40%	-0.81%	-0.78%	-0.41%	-0.24%
	(-1.68)	(-1.08)	(-0.84)	(-1.61)	(-1.22)	(-1.16)	(-0.67)
NF5	-0.85%***	-0.81%**	-0.87%*	-1.28%*	-0.29%	-0.56%	-0.37%
	(-2.86)	(-2.07)	(-1.94)	(-1.88)	(-0.49)	(-1.68)	(-1.09)
NF1-NF5	0.78%***	0.68%*	0.48%	1.71%***	-0.04%	0.24%	0.80%**
	(2.80)	(1.66)	(1.10)	(2.74)	(-0.06)	(0.88)	(2.31)

* Significant at the 90 percent confidence level.
** Significant at the 95 percent confidence level.
*** Significant at the 99 percent confidence level.

Table 3.4 Aggregate Characteristic-Timing Performance, Conditioning on Net Investor Flows and Active Style Drift

This table reports the aggregate characteristic-timing performance conditioning on net investor flows and active style drift. Net investor flows are calculated as estimated percentage change in TNA adjusted for investment return and mutual fund mergers. Active style drift is calculated following Wermers (2012) as the difference of style quintile numbers along size, book-to-market and momentum dimensions. For each month, mutual funds are divided into five quintiles based on net investor flows. For each of net investor flows portfolio, mutual funds are then divided into quintiles according to active style drift. The t-statistics are presented below in parentheses.

	SD1 (Large Drift)	**SD2-SD4**	**SD5 (Small Drift)**	**ALL**	**SD1-SD5**
NF1 (Outflow)	-0.92%	0.21%	-0.02%	-0.07%	-0.91%
	(-1.63)	(0.64)	(-0.05)	(-0.23)	(-1.32)
NF2-NF4	-0.04%	-0.38%	-0.29%	-0.30%	0.25%
	(-0.12)	(-1.43)	(-0.82)	(-1.11)	(0.79)
NF5 (Inflow)	-1.76%***	-0.54%*	-0.90%**	-0.85%***	-0.88%
	(-2.78)	(-1.75)	(-2.46)	(-2.86)	(-1.34)
ALL	-0.66%**	-0.17%	-0.57%*	-0.37%	-0.08%
	(-2.31)	(-0.70)	(-1.80)	(-1.57)	(-0.26)
NF1-NF5	0.86%	0.75%**	0.88%**	0.78***	-
	(1.21)	(2.58)	(2.50)	(2.80)	-

* Significant at the 90 percent confidence level.
** Significant at the 95 percent confidence level.
*** Significant at the 99 percent confidence level.

Table 3.5 Characteristic-Timing Performance for Buying and Selling Are Related to Trade Motivations (1)

This table reports the characteristic-timing performance for buying and selling, conditioning on motivation scores including buy flow score (*BF*) and sell flow score (*SF*). Based on Alexander *et al* (2007), the proximities for buying and selling motivation are calculated based on the net investor flows, total buying volume and total selling volume. Specifically, buy flow score for fund i at time t is measured as the difference between total dollar volume for buying at time t and net investor flows at time t, divided by total net assets at time t-1. And sell flow score for fund i at time t is calculated as the sum of total dollar volume for selling at time t and net investor flow at time t, divided by total net assets at time t-1. For each month, mutual funds are divided into five quintiles based on the buy flow score and the sell flow score. The times series average of cross-sectional average of buying and selling characteristic-timing performance are reported for all mutual fund samples and sub-samples of different investment objectives. The t-statistics are presented below in parentheses.

	All Funds	**Growth**	**Growth &Income**	**Income**	**Micro-Cap**	**Small-Cap**	**Mid-Cap**
				Buying			
BF1	1.90%**	2.04%**	1.76%**	1.66%*	2.02%**	2.21%**	2.27%**
	(2.19)	(2.25)	(2.25)	(1.95)	(1.99)	(2.16)	(2.12)
BF2	1.15%*	0.87%	0.77%	1.10%*	1.39%	1.66%**	2.09%**
	(1.70)	(1.45)	(1.08)	(1.71)	(1.54)	(2.17)	(2.28)
BF3	0.97%*	0.77%	1.03%*	0.80%	1.00%	1.16%*	1.66%*
	(1.76)	(1.23)	(1.72)	(1.48)	(1.01)	(1.79)	(1.78)
BF4	0.93%	0.58%	0.53%	1.14%*	1.00%	1.18%*	1.05%
	(1.61)	(0.96)	(1.06)	(1.83)	(1.09)	(1.83)	(1.38)
BF5	0.95%	0.31%	0.97%	0.79%	1.04%	1.58%*	1.80%*
	(1.16)	(0.43)	(1.30)	(0.84)	(0.84)	(1.80)	(1.93)
BF1-BF5	0.93%***	1.70%**	0.78%**	0.86%**	0.96%	0.63%**	0.46%
	(4.03)	(2.49)	(2.01)	(2.33)	(1.47)	(2.09)	(0.91)
				Selling			
SF1	-1.57%*	-1.36%	-1.80%***	-1.67%**	-1.11%	-1.62%*	-1.97%*
	(-1.94)	(-1.49)	(-2.69)	(-2.53)	(-0.84)	(-1.79)	(-1.95)
SF2	-1.21%*	-1.40%**	-0.72%	-0.91%*	-1.34%	-1.44%*	-1.25%*
	(-1.92)	(-2.01)	(-1.33)	(-1.81)	(-1.14)	(-1.90)	(-1.71)
SF3	-1.45%**	-1.31%*	-1.60%***	-1.36%**	-1.32%	-1.32%*	-2.10%*
	(-2.20)	(-1.86)	(-2.66)	(-2.11)	(-1.21)	(-1.85)	(-1.81)
SF4	-1.63%**	-1.29%*	-1.76%**	-1.82%**	-1.95%*	-1.93%**	-2.39%**
	(-2.08)	(-1.65)	(-2.29)	(-2.35)	(-1.78)	(-2.21)	(-2.19)
SF5	-2.24%**	-2.13%**	-2.36%***	-2.23%**	-2.08%	-2.70%**	-2.64%**
	(-2.16)	(-2.00)	(-2.68)	(-2.14)	(-1.57)	(-2.13)	(-2.10)
SF1-SF5	0.69%**	0.78%*	0.58%	0.58%	0.99%	1.11%**	0.69%
	(2.01)	(1.80)	(1.40)	(0.83)	(1.13)	(2.29)	(1.42)

* Significant at the 90 percent confidence level.
** Significant at the 95 percent confidence level.
*** Significant at the 99 percent confidence level.

Table 3.6 Characteristic-Timing Performance for Buying and Selling Are Related to Trade Motivations (2)

The dependent variables are the characteristic-timing performance for buy and sell portfolio for mutual funds. Valuation is an indicator variable equal to one for every month the mutual fund is identified as valuation motivated (high flow score for buying and selling, respectively), zero otherwise; Liquidity is an indicator variable equal to one for every month the mutual fund is identified as liquidity driven (low flow score for buying and selling, respectively), zero otherwise. *log(AGE)* is the natural logarithm of age in years since first offer date. *log(TNA)* is the natural logarithm of total net assets under management in millions of dollars. *Expenses* is fund expense ratio in percentage per year. *Turnover* is the fund turnover ratio in percentage per year. *Flow* is estimated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. *Fee* is the fund management fee in percentage per year. *Size*, *btm*, and *Momentum* are quintile number of fund style characteristics along the size, book-to-market and momentum dimensions. All these control variables are demeaned. *Flow* and *Turnover* are winsorized at 1% level. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. *4th Quarter* is an indicator variable equal to one for every month is in the fourth quarter, and zero otherwise. The data are monthly and cover the period from 2003 to 2013. Standard errors (in parentheses) are clustered by fund and time.

	Buying			Selling		
	(1)	(2)	(3)	(4)	(5)	(6)
Valuation	0.065***	0.070***	0.070***	0.012*	0.030***	0.043***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)
Liquidity	-0.025***	-0.033***	-0.047***	-0.110***	-0.124***	-0.121***
	(0.006)	(0.006)	(0.006)	(0.009)	(0.010)	(0.009)
Log(AGE)		0.107***	0.086***		-0.124***	-0.104***
		(0.014)	(0.013)		(0.015)	(0.014)
Log(TNA)		-0.093***	-0.123***		0.104***	0.136***
		(0.007)	(0.007)		(0.080)	(0.007)
Expenses		6.983	-3.421		-5.850	5.223
		(4.708)	(3.689)		(4.500)	(3.540)
Turnover		0.052***	0.064***		-0.032***	-0.045***
		(0.010)	(0.009)		(0.012)	(0.012)
Flow		0.205***	0.159***		-0.277***	-0.232***
		(0.043)	(0.042)		(0.043)	(0.041)
Fee		-0.019***	-0.015***		0.017***	0.013**
		(0.003)	(0.004)		(0.004)	(0.006)
Size		0.110***	0.107***		-0.136***	-0.129***
		(0.028)	(0.027)		(0.030)	(0.029)
btm		-0.065***	-0.052***		0.108***	0.094***
		(0.020)	(0.019)		(0.020)	(0.019)
Momentum		-0.110***	-0.060***		0.115***	0.062***
		(0.014)	(0.014)		(0.015)	(0.015)
Recession			-0.360***			0.388***
			(0.011)			(0.012)
4th Quarter			-0.001			-0.025***
			(0.005)			(0.005)
Constant	0.101***	0.100***	0.166***	-0.110***	-0.108***	-0.172***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Obs	144,926	141,767	141,767	144,926	141,767	141,767

Table 3.7 Characteristic-Timing Performance for Buying and Selling, Conditioning on Flow Score and Trade Size

This table reports the buying and selling characteristic-timing performance conditioning on flow metrics and trade size. Following Alexander *et al* (2007), the flow metrics for buying and selling motivation are calculated based on the net investor flows, total buying volume and total selling volume. Specifically, buy flow score for fund i at time *t* is measured as the difference between total dollar volume for buying at time t and net investor flows at time *t*, divided by total net assets at time *t-1*. Sell flow score for fund i at time t is measured as the sum of total dollar volume for sell at time *t* and net investor flows at time *t*, divided by total net assets at time *t-1*. The net investor flows are calculated based on the changes total net assets under management adjusted for investment returns and mutual fund mergers. For each month, mutual funds are divided into five quintiles based on the buy and sell flow score. For each of the buy and selling portfolio, trades are divided into quintiles according to their dollar value. The t-statistics are presented below in parentheses.

	TS1 (Large)	TS2	TS3	TS4	TS5 (Small)	TS1-TS5	
Panel A Buy							
BF1	1.61%**	1.06%**	0.65%**	0.45%**	0.16%*	1.45%**	
	(1.99)	(2.42)	(2.11)	(2.31)	(1.68)	(1.97)	
BF2	1.14%*	0.67%*	0.49%*	0.25%	0.12%*	1.01%*	
	(1.85)	(1.95)	(1.89)	(1.38)	(1.77)	(1.80)	
BF3	0.80%	0.53%*	0.36%*	0.27%*	0.05%	0.75%	
	(1.54)	(1.93)	(1.70)	(1.93)	(0.88)	(1.56)	
BF4	0.74%*	0.43%*	0.26%	0.15%	0.03%	0.71%**	
	(1.88)	(1.94)	(1.61)	(1.22)	(0.45)	(2.05)	
BF5	0.64%*	0.30%	0.28%**	0.17%*	0.05%	0.58%*	
	(1.83)	(1.56)	(2.10)	(1.87)	(1.15)	(1.83)	
BF1-BF5	0.96%*	0.76%**	0.37%*	0.28%**	0.11%	-	
	(1.77)	(2.55)	(1.74)	(2.13)	(1.26)	-	
BF1/TS1-BF5/TS5							1.56%*
							(1.98)
Panel B Sell							
SF1	-0.87%**	-0.42%*	-0.35%**	-0.26%**	-0.14%**	-0.73%**	
	(-2.13)	(-1.74)	(-2.01)	(-2.24)	(-1.99)	(-2.08)	
SF2	-1.11%**	-0.49%*	-0.29%	-0.18%*	-0.11%	-1.00%**	
	(-2.21)	(-1.75)	(-1.43)	(-1.68)	(-1.45)	(-2.29)	
SF3	-1.11%*	-0.55%*	-0.32%	-0.19%	-0.10%	-1.02%*	
	(-1.78)	(-1.67)	(-1.32)	(-1.36)	(-1.44)	(-1.78)	
SF4	-1.32%*	-0.75%*	-0.51%**	-0.29%**	-0.10%	-1.24%*	
	(-1.76)	(-1.94)	(-2.02)	(-2.29)	(-1.44)	(-1.75)	
SF5	-2.73%***	-1.29%***	-0.87%***	-0.44%**	0.03%	-2.76%***	
	(-2.90)	(-2.82)	(-3.03)	(-2.39)	(0.44)	(-3.03)	
SF1-SF5	1.91%***	0.88%***	0.53%***	0.17%	-0.17%**	-	
	(3.04)	(3.11)	(3.21)	(1.56)	(-2.50)	-	
SF1/TS1-SF5/TS5							-0.89%**
							(-2.37)

* Significant at the 90 percent confidence level.
** Significant at the 95 percent confidence level.
*** Significant at the 99 percent confidence level.

Table 3.8 Characteristic-Timing Performance of Good Sellers

The dependent variables are the characteristic-timing performance for buy and sell portfolio for mutual funds. *Top* is the indicator variable equal to one for all funds whose selling performance when sales are valuation motivated is in the highest 25th percentile of the distribution, and zero otherwise. *log(AGE)* is the natural logarithm of age in years since first offer date. *log(TNA)* is the natural logarithm of total net assets under management in millions of dollars. *Expenses* is fund expense ratio in percentage per year. *Turnover* is the fund turnover ratio in percentage per year. *Flow* is estimated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. *Fee* is the fund management fee in percentage per year. *Size*, *btm*, and *Momentum* are quintile number of fund style characteristics along the size, book-to-market and momentum dimensions. All these control variables are demeaned. *Flow* and *Turnover* are winsorized at 1% level. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. *4th Quarter* is an indicator variable equal to one for every month is in the fourth quarter, and zero otherwise. The data are monthly and cover the period from 2003 to 2013. Standard errors (in parentheses) are clustered by fund and time.

	Selling			Buying		
	(1)	(2)	(3)	(4)	(5)	(6)
Top	0.135***	0.135***	0.112***	0.096***	0.087***	0.072***
	(0.011)	(0.011)	(0.011)	(0.017)	(0.017)	(0.016)
Log(AGE)		-0.049***	-0.046***		0.218***	0.205***
		(0.017)	(0.017)		(0.031)	(0.028)
Log(TNA)		0.067***	0.083***		-0.145***	-0.186***
		(0.009)	(0.009)		(0.016)	(0.015)
Expenses		5.567	11.807***		11.664	-3.353
		(4.090)	(3.763)		(8.255)	(5.921)
Turnover		0.004	-0.009		0.098***	0.111***
		(0.019)	(0.018)		(0.023)	(0.022)
Flow		-0.254***	-0.245***		0.097	0.022
		(0.048)	(0.046)		(0.092)	(0.090)
Fee		-0.013	-0.016		-0.016***	-0.013***
		(0.014)	(0.013)		(0.003)	(0.005)
Size		-0.063	-0.054		0.162***	0.168***
		(0.039)	(0.039)		(0.061)	(0.058)
btm		0.035	0.025		-0.170***	-0.143***
		(0.024)	(0.023)		(0.040)	(0.038)
Momentum		0.065***	0.034*		-0.175***	-0.091***
		(0.019)	(0.019)		(0.032)	(0.031)
Recession			0.277***			-0.509***
			(0.019)			(0.024)
4th Quarter			-0.079***			-0.084***
			(0.008)			(0.011)
Constant	-0.130***	-0.113***	-0.127***	0.143***	0.145***	-0.265***
	(0.004)	(0.005)	(0.005)	(0.007)	(0.009)	(0.008)
Obs	46,868	46,202	46,202	46,676	46,094	46,094

Table 3.9 Characteristic-Timing Performance of Good Buyers

The dependent variables are the characteristic-timing performance for buy and sell portfolio for mutual funds. *Top* is the indicator variable equal to one for all funds whose buying performance when purchases are valuation motivated is in the highest 25th percentile of the distribution, and zero otherwise. *log(AGE)* is the natural logarithm of age in years since first offer date. *log(TNA)* is the natural logarithm of total net assets under management in millions of dollars. *Expenses* is fund expense ratio in percentage per year. *Turnover* is the fund turnover ratio in percentage per year. *Flow* is estimated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} * (1 + RET_{i,t}) - MGN_{i,t}$ to $TNA_{i,t-1}$. *Fee* is the fund management fee in percentage per year. *Size*, *btm*, and *Momentum* are quintile number of fund style characteristics along the size, book-to-market and momentum dimensions. All these control variables are demeaned. *Flow* and *Turnover* are winsorized at 1% level. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. *4th Quarter* is an indicator variable equal to one for every month is in the fourth quarter, and zero otherwise. The data are monthly and cover the period from 2003 to 2013. Standard errors (in parentheses) are clustered by fund and time.

	Buying			Selling		
	(1)	(2)	(3)	(4)	(5)	(6)
Top	0.315***	0.310***	0.307***	-0.020	-0.017	-0.011
	(0.017)	(0.017)	(0.016)	(0.012)	(0.012)	(0.012)
Log(AGE)		0.213***	0.200***		-0.049***	-0.046***
		(0.030)	(0.027)		(0.017)	(0.017)
Log(TNA)		-0.137***	-0.180***		0.070***	0.086***
		(0.015)	(0.014)		(0.009)	(0.009)
Expenses		12.035	-2.999		6.332	12.915***
		(7.799)	(5.621)		(4.155)	(3.807)
Turnover		0.079***	0.091***		0.001	-0.012
		(0.023)	(0.021)		(0.019)	(0.019)
Flow		0.068	-0.012		-0.245***	-0.237***
		(0.089)	(0.087)		(0.049)	(0.047)
Fee		-0.017***	-0.013***		-0.015	-0.018
		(0.003)	(0.005)		(0.015)	(0.013)
Size		0.164***	0.172***		-0.067	-0.057
		(0.060)	(0.057)		(0.040)	(0.040)
btm		-0. 177***	-0.152***		0.029	0.020
		(0.039)	(0.037)		(0.025)	(0.024)
Momentum		-0.173***	-0.090***		0.069***	0.035*
		(0.032)	(0.031)		(0.020)	(0.020)
Recession			-0.512***			0.292***
			(0.024)			(0.020)
4th Quarter			-0.083***			-0.079***
			(0.011)			(0.008)
Constant	0.091***	0.092***	0.210***	-0.092***	-0.076***	-0.100***
	(0.006)	(0.007)	(0.007)	(0.004)	(0.005)	(0.005)
Obs	46,676	46,094	46,094	46,868	46,202	46,202

Table 3.10 Aggregate Characteristic-Timing performance, Good Sellers vs. Good Buyers

The dependent variables are the aggregate characteristic-timing performance for top sellers and top buyers, respectively. *Top* is the indicator variable equal to one for all funds whose selling (buying) performance when sales (purchases) are valuation motivated is in the highest 25th percentile of the distribution, and zero otherwise. *log(AGE)* is the natural logarithm of age in years since first offer date. *log(TNA)* is the natural logarithm of total net assets under management in millions of dollars. *Expenses* is fund expense ratio in percentage per year. *Turnover* is the fund turnover ratio in percentage per year. *Flow* is estimated investor flows as the ratio of $TNA_{i,t} - TNA_{i,t-1} * \left(1 + RET_{i,t}\right) - MGN_{i,t}$ to $TNA_{i,t-1}$. *Fee* is the fund management fee in percentage per year. *Size*, *btm*, and *Momentum* are quintile number of fund style characteristics along the size, book-to-market and momentum dimensions. All these control variables are demeaned. *Flow* and *Turnover* are winsorized at 1% level. *Recession* is an indicator variable equal to one for every month the economy is in a recession according to the NBER, and zero otherwise. *4th Quarter* is an indicator variable equal to one for every month is in the fourth quarter, and zero otherwise. The data are monthly and cover the period from 2003 to 2013. Standard errors (in parentheses) are clustered by fund and time.

	Good seller			Good buyer		
	(1)	(2)	(3)	(4)	(5)	(6)
Top	0.025***	0.026***	0.026***	0.009	0.008	0.008
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Log(AGE)		-0.019**	-0.024***		-0.019**	-0.024***
		(0.008)	(0.008)		(0.008)	(0.008)
Log(TNA)		0.010**	0.012***		0.010**	0.013***
		(0.004)	(0.004)		(0.004)	(0.004)
Expenses		0.519	1.205		0.486	1.186
		(1.955)	(1.980)		(1.957)	(1.982)
Turnover		0.024***	0.023***		0.024***	0.023***
		(0.008)	(0.008)		(0.008)	(0.008)
Flow		-0.010	-0.010		-0.010	-0.010
		(0.026)	(0.026)		(0.026)	(0.026)
Fee		-0.000	-0.000		-0.000	-0.000
		(0.002)	(0.002)		(0.002)	(0.002)
Size		-0.031**	-0.025*		-0.031**	-0.025*
		(0.014)	(0.014)		(0.014)	(0.014)
btm		0.049***	0.049***		0.049***	-0.049***
		(0.014)	(0.014)		(0.014)	(0.014)
Momentum		0.003	0.000		0.004	0.000
		(0.010)	(0.010)		(0.010)	(0.010)
Recession			0.031***			0.031***
			(0.008)			(0.008)
4th Quarter			-0.035***			-0.035***
			(0.005)			(0.005)
Constant	-0.034***	-0.034***	-0.030***	-0.030***	-0.030***	-0.026***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Obs	144,926	141,767	141,767	144,926	141,767	141,767

Table 3.11 Fund Characteristics for Good Sellers

Top is the indicator variable equal to one for all funds whose selling performance when sales are valuation motivated is in the highest 25th percentile of the distribution, and zero otherwise. *AGE* is age in years since first offer date. *TNA* is the total net assets under management in millions of dollars. *Expenses* is fund expense ratio in percentage per year. *Turnover* is the fund turnover ratio in percentage per year. *Fee* is the fund management fee in percentage per year. *ASD* is the active style drift calculated according to Wermers (2012) as the changes in quintile number of fund style characteristics along the size, book-to-market and momentum dimensions. *Stock Number* is the total number of stock held by mutual funds. *Top1-Top0* is the difference between the mean values of the groups for which *Top* equals to one and zero, respectively. *p*-value measure statistical significance of the difference. The data are monthly and cover the period from 2003 to 2013.

	Good seller			Others			Difference	
	Mean	Stdev.	Median	Mean	Stdev.	Median	Top1-Top0	*p*-value
Age	14.65	13.01	11	15.30	12.55	12	-0.65	0.000
TNA	1397.58	4072.90	246.60	1567.89	6592.69	288.4	-170.31	0.000
Expenses	1.24	0.45	1.20	1.19	0.37	1.20	0.05	0.000
Fee	0.73	0.35	0.75	0.71	0.36	0.74	0.02	0.000
Turnover	105.38	103.13	81.00	73.17	66.29	58.00	32.21	0.000
ASD	0.27	0.27	0.18	0.19	0.23	0.13	0.07	0.000
Stock Number	116.96	132.73	82	136.70	172.31	88	-19.74	0.000

Chapter 4

Fund Manager Overconfidence and Investment Performance

4.1 Introduction

Conventional finance predominantly views mutual fund managers as a class of professional investors who gather and process information efficiently and make investment decisions in a more rational way than inexperienced investors. The majority of research focuses on investigating whether fund managers have specific skills, exploring whether particular investment strategies generate superior returns, and testing whether the market is efficient. In consequence, little attention has been paid to looking at fund managers as human beings who are usually susceptible to behavioral biases and heuristics such as overconfidence.

The nature of professional experience in asset management can easily expose mutual fund managers to the risk of becoming overconfident: fund managers are constantly under intensive competition to outperform peer managers who are equally qualified; they are swamped with incomplete information that is often conflicting and open to competing interpretations (Tuckett and Taffler, 2012). In the end, investment decisions are often made by relying on subjective judgements and beliefs based on managers' private information which can only be verified with vague and delayed feedback. Consequently, fund managers can be particularly susceptible to the self-serving attribution bias. Previous psychological studies suggest that biased self-attribution can leads to individuals to attribute positive outcome to their own skills, but attribute bad outcomes to chance (e.g., Hastorf *et al*, 1970; and Miller and Ross, 1975). Self-serving attribution bias leads fund managers to falsely attribute good investment performance of their investment decisions to their good skills, while attributing poor past performance to bad luck. Fund managers become more confident after a good past performance, but not less confident to the same extent after a poor past performance (e.g., Gervais and Odean, 2001), which eventually leads 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, leading to excessive deviation from their benchmark indices. Such portfolio allocation decisions driven by false beliefs about their investment skills and information precision should eventually harm portfolio performance.

To investigate whether fund managers are prone to overconfidence, this chapter uses 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 past performance and managerial confidence. By analyzing a large sample of U.S. domestic actively managed equity mutual funds, we find a clear U-shaped non-linear relationship between past performance of mutual 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 choose high Active Share levels in the subsequent period. One possible explanation is that these poorly performing fund managers are in effect engaging in gambling, perhaps in an attempt to increase the possibility of catching up their positions in the future. Consistently, we observe that fund managers are more likely to increase their Active Share level following good performance. Overall, these results strongly support our main hypothesis that good performance leads to overconfidence as measured by a higher Active Share level. Like inexperienced 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, this chapter 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 more rational (i.e., 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. Furthermore, there is 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.

This chapter also sheds new light on the determinants of fund flows by looking at how investors respond 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 attributing 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 their investment skills of fund managers. As a consequence, investors irrationally chase overconfident fund managers, flocking to funds with extremely high Active Share when observing good fund performance but failing to flee from these funds to the same extent following poor fund performance.

This chapter contributes to four strands of the literature. First, 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. Experimental studies suggest that professional investors are more overconfident than inexperienced participants (Griffin and Tversky, 1992; Glaser, Langer and Weber, 2010). 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 Puenzi (2011) report that fund managers trade more excessively after good performance. A recent working paper by Choi and Lou (2010) uses Active Share as a proxy of overconfidence and uses the sum of positive (negative) past performance as a proxy for confirming (disconfirming) market signals. They find evidence to show 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 (2012) apply content analysis on the reports managers write to their investors and show that mutual fund managers who generate superior past performance become overconfident. Additionally, this chapter 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 or not and look at the investor reaction. Notable exceptions are Bär, Kempf and Ruenzi (2011) who were among the first to explore the behavioral differences between solo- and team-managed funds and show that team-managed funds follows less extreme investment styles and hold less industry concentrated portfolios, and eventually, are less like to experience extreme performance outcomes.

Second, this chapter contributes to the literature on mutual fund performance. Despite the extensive literature examining overconfidence and the potential impact of overconfidence among retail investors and corporate managers, there is a limited amount of work that looks directly at the role of confidence on subsequent performance. This chapter is one of the first attempts to explore the potential non-linear relationship between confidence level and future performance. A close related work by Eshraghi and Taffler (2012) uses content analysis to test whether overconfidence is associated with diminished subsequent performance. Similar to our findings, these authors provides strong evidence of an inverted U relationship between confidence and subsequent performance and they find a trading strategy, based on shorting on overconfident funds and going long on normal confident funds generating superior returns.

Third, this chapter 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 Zheng, 2005) and other documented determinants of fund flows including 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, 2015). This chapter 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 remaining sections of the chapter are organized as follows. In Section 4.2, this chapter reviews recent related literature on overconfidence. Section 4.3 describes the related methodology used in this chapter. Section 4.4 presents data source and sample construction. Section 4.5 shows the empirical analysis and results and Section 4.6 concludes.

4.2 Literature Review

Traditional finance seeks to understand the financial market by predominately assuming that 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. A large number of studies in recent 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 to show 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) seek 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, *et al*, 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.

Although institutional investors such as mutual funds play an increasingly dominant role in the financial market, there are only few studies that analyze the behaviors of these professional investors who can also be susceptible to behavioral biases and heuristics such as overconfidence. Puetz and Ruenzi (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 to show 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 Puenzi (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. They find evidence to this hypothesis by mainly testing the relationship between the sums 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 (2012) 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 outperform 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 well-documented psychological attributes that can be highly influential in shaping decisions of economic agents. In fact, Plous (1993) suggests that 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 no 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 self-serving attribution bias and overconfidence, and whether and to what extent such biases might impact investment performance.

4.3 Methodology

4.3.1 Measuring Fund Manager Confidence Level

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 place 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 is thencalculated 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 would then 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%.[1] 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.

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 no easy task. Petajisto (2013) uses 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 can also 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 chapter 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.

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

4.3.2 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 chapter 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 chapter, we run the regression for each fund *i* and each year and collect the time series of the estimated intercept for each fund *i* as the risk-adjusted performance over time. This chapter 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 chapter 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.

4.3.3 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 chapter 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 chapter 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 chapter 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.

4.4 Data and Sample

4.4.1 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 U.S. open-end mutual fund. Following the standard procedure in the literature, for funds with multiple share classes with the same back-up portfolio, this chapter computes the sum of total net assets under management (tna) in 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 chapter 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 chapter selects the variables from the share class with the highest total net assets and longest history.

This chapter maps the Thomson Reuters Mutual Fund Holdings Database with the CRSP Mutual Fund Database by using the MFLINKS Database. The 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 chapter also tries to correct any matching errors after this standard data merging procedure by looking manually at fund names in both databases.

4.4.2 Active Share Data

Active Share data are obtained from Petajisto's Website,[2] which is the updated main data set from Petajisto (2013). To calculate active share, one needs data on portfolio

2 http://www.petajisto.net/data

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).

4.4.3 Stock Price and Accounting Data

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[3] 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 chapter 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 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.

4.4.4 Sample Selection

The focus of the analysis is on actively managed U.S. domestic equity mutual funds for which the holdings data are most complete and reliable. This chapter follows and modifies the procedure of Kacperczyk *et al* (2008) to select U.S. domestic equity mutual funds. This chapter 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 chapter requires average equity holdings (avrcs) to be at least 70% and the percentage of matched U.S. stock holdings to be at least 60%. This chapter 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 chapter eliminates 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 U.S. domestic equity mutual fund samples in the period 1980 to 2009. Appendix A provides further details on the sample selection.

4.4.5 Summary Statistics

Table 4.1 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 4.2 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 4.1. As we can see, on average micro-cap and small-cap mutual funds (or aggressive growth-oriented funds) have a disproportionately 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.

4.5 Empirical Results

4.5.1 Overconfidence and Past Fund Performance

This chapter 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 chapter 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 follows:

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

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 chapter 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 chapter 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 winsorise Flow and Turnover at the 1% level.[4] We also include year dummies to capture any time fixed effect and market segment dummies to control segment fixed effects.

Table 4.3 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).

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

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 performance attracts investor flows and more importantly, ordinal performance measures explain inflows better than cardinal performance measures. 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 chapter follows this approach to capture the impact of past performance on the confidence level of mutual fund managers, reflected by the deviation from their benchmark indices. Specifically, this chapter 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 chapter runs the following regression:

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

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 4.4 summarises the results of the regressions of Active Share on past performance rank. Consistent with what we observe in Table 4.3, 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 chapter expects a positive relationship between past performance and Active Share level among very successful fund managers with superior past performance. Second, in an attempt 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 a 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 chapter expects 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 chapter uses two alternative modelling approaches to capture the potential U-shape relationship.

First, this chapter 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:

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

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 chapter estimates a quadratic relationship between past performance and Active Share by modelling past performance in linear and quadratic terms:

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

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 chapter 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 4.5. 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 are 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% ($0.60 \times 0.2 = 0.12$).

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% ($-0.43 \times 0.2 = -0.086$), 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 4.6 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 4.5.

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 4.7. 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 do teams, because the opinions of team members are likely to shift towards the opinion of the dominant person, which eventually leading to aggressive decisions. If this is case, solo managed funds might be less likely to be at risk of becoming overconfident after good past performance than team managed funds who are prone to group think bias. On the other hand, the diversification of opinions hypothesis suggests that teams are more rational than individuals (Cooper and Kagel, 2005; Kocher and Sutter, 2005) and they make less extreme decisions (Sah and Stiglitz, 1986 and 1988). If this is true, one might expect that individuals are more likely to be at risk of being overconfident after good past performance and of gambling after poor past performance. 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 chapter 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:

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

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 are therefore less likely to become 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 the diversification opinion hypothesis, we should observe that solo managed funds act more irrationally, and therefore, a negative (positive) coefficient is expected for the interaction term of bottom (top) performance quintile. Model (5) results are presented in Table 4.8.

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 - Macbeth (1973) regression method at similar significant levels. Therefore, our findings provide strong evidence to show 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.

4.5.2 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 to lead eventually 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 reflects 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 increasingly seem to 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 thereby, to 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 an 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 chapter 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) have disproportionately 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 as having high Active Share among its peer funds.

To overcome this structural difference in Active Share level across different investment objective categories, this chapter 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 chapter 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 is 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 to 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 the 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 chapter 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 chapter 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.[5] 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

[5] 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.

quintile, the three middle quintiles and the top quintile of Active Share rank are presented in Table 4.9. 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 (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 chapter applies an alternative approach by replacing the piecewise linear approach by dummies indicating in which decile of Active Share funds:

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

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 4.10 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 a normal level of confidence, as reflected by moderate Active Share levels, is economically meaningful. In particular, in holding other effects constant, the normally confident funds that belong 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 magnitude of the effect of Active Share on 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 chapter also applies the quadratic specification as an additional test to confirm the non-linear relationship between Active Share rank and subsequent performance:

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

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 4.11 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 4.12. 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.

4.5.3 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 chapter 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 4.13.

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 ($= 2.267 \times 0.2 = 0.453$).[6] 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 4.14 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 chapter 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 4.15 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

[6] 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.

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 4.16 show that changes in Active Share rank are positively related with performance dispersion. These findings are thus consistent with the expectation that mutual fund manager overconfidence is associated with greater performance dispersion as a measure of risk.

Overall, we find strong evidence to show 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.

4.5.4 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 chapter estimates the following regression:

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

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 chapter 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 chapter winsorises flow and turnover at the 1% level. This chapter 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 4.17 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:

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

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 chapter 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 4.18.

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. This suggest 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 within 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, namely 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 the 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 is 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 response 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.

4.6 Conclusion

In this chapter, I examine overconfidence among mutual fund managers. I investigate whether mutual fund managers are subject to self-serving attribution bias, and whether fund managers become overconfident after good past performance. Using U.S. 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 too 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 to show 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 (2010) which illustrates the log-change of a measure corresponding to overconfidence bias.

This chapter also sheds 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 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.

Figure 4.1 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.

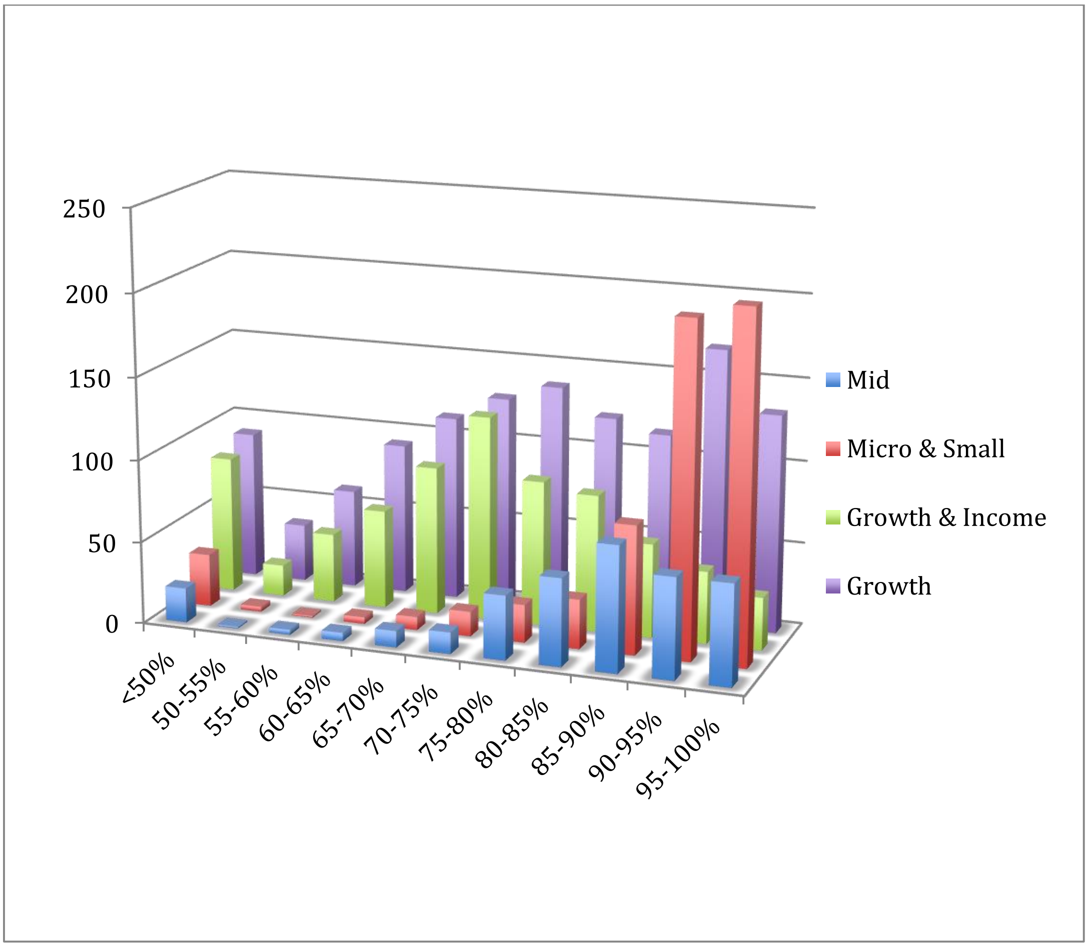

Table 4.1 Descriptive Statistics of Mutual Fund Samples

The table below reports the summary statistics of a total of 2740 unique U.S. 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 U.S. Database. CRSP investment objective variable (crsp_obj_cd) is used to filter U.S. 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 4.2 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 4.3 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 chapter 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 chapter 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 4.4 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 chapter 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 chapter 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 4.5 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 chapter 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 chapter 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 4.6 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 chapter 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 chapter 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 4.7 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 chapter 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 chapter 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 4.8 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 chapter 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 chapter 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 4.9 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 chapter 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 chapter 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 4.10 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 chapter 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 chapter 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 4.11 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 chapter 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 chapter 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 4.12 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 chapter 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 chapter 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 4.13 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 chapter 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 chapter 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 4.14 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 chapter 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 chapter 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 4.15 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 chapter 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 chapter 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 4.16 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 chapter 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 chapter 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 4.17 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 chapter 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 chapter 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 4.18 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 chapter 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 chapter 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

Chapter 5

Concluding Remarks

The consensus from extant research is that equity mutual fund managers, as a representative group of professional investors, fail to outperform passive benchmarks (e.g., Jensen, 1968; Malkiel, 1995; Carhart, 1997) and are unable to time the market or risk factors appropriately (e.g., Treynor and Mazuy, 1966; Henriksson and Merton, 1981; Daniel, *et al*, 1997). Research into fund performance persistence also provides disheartening results in that superior fund performance appears to be largely unpredictable from past performance (e.g., Gruber, 1996; Carhart, 1997; Bollen and Busse, 2005). By using a rational competitive market model, Berk and Green (2004) offer the explanation that the superior performance of skilled fund managers is quickly bid away by fund investors, leading to weakening in performance persistence. However, their arguments are not able to explain the stronger evidence consistent with performance persistence among poorly performing funds (e.g., Teo and Woo, 2001; Kosowski *et al*, 2006; Barras *et al*, 2010; and Cuthbertson *et al*, 2008). Cuthbertson *et al* (2008) suggest that most inferior funds are not unlucky; rather these funds exhibit "bad skill". Together these disappointing findings raise some fundamental questions: Why do mutual funds underperform? What skills do fund managers really possess? Are fund manager underperformance and "bad skill" due to susceptibility to behavioral biases and heuristics?

This thesis sets out to explore potential sources of fund manager underperformance. In the second chapter, it examines whether mutual fund managers possess differential skill attributes, and in particular, whether they exhibit "bad skill" that can potentially mask "good skill" and lead to underperformance. Motivated by the findings of irrational selling decisions among individual investors from the behavioural finance literature (e.g., Shefrin and Statman, 1985; Odean, 1998; Barberis and Thaler, 2003), my second chapter places emphasis on fund manager trading skills, namely buying and selling abilities. Following Chen *et al* (2013) who document distinct trading skills among a relative small number of "star" mutual fund managers, I decompose aggregate characteristic-timing performance into buying and selling components. By analysing a large sample of actively managed equity mutual funds from 2003 to 2013, my results show that on average, mutual fund managers exhibit positive characteristic-timing ability when buying stocks but negative characteristic-timing ability when selling stocks. Further, persistence tests demonstrate that these differential trading skills are not merely due to chance: fund managers who exhibit superior characteristic-timing performance when buying stocks continue to perform buying tasks well, while those who are poor performers in selling continue to underperform in their selling activity in the near term. Consistent with my hypothesis, these findings suggest that the lack of evidence of timing ability in the literature masks the distinct trading abilities that fund managers really possess. Moreover, using changes in portfolio styles along the size, book-to-market, and momentum dimensions (i.e., active style drift) as a proxy for strength of conviction, this chapter reveals an inverted U-shaped relationship between fund manager conviction and subsequent overall characteristic-timing performance. In particular, when fund managers aggressively engage in active style drift, their poor selling ability is overwhelming, leading to negative aggregate performance.

The third chapter of this thesis advances the investigation of characteristic-timing performance and trading skills by considering the fact that fund managers are often forced to trade in response to investor flows. Consistent with theoretical predictions from rational expectation models (e.g., Grossman, 1976; Grossman and Stiglitz, 1980; Hellwig, 1980; and Verrcecchia, 1982), a number of recent studies have shown that liquidity-induced trading imposes indirect trading costs on fund managers (e.g., Chordia, 1996; Edelen, 1999; Nanda *et al*, 2000; Alexander *et al*, 2007). Unlike Edelen (1999) who uses a return-based approach to capture the adverse effect of fund flows to market timing performance, my results reveal that fund managers exhibit negative characteristic-timing performance only when they experience significant fund inflows, suggesting that excessive cash holdings from fund inflows do not provide financial flexibility but impose trading costs on fund managers. However, there is some evidence to indicate that negative characteristic-timing performance is at least partly driven by poor timing ability when fund manager conviction is added into the analysis. More importantly, by conditioning fund trades on the direction and magnitude of fund flows, two key findings emerge. First, consistent with the theoretical predictions, liquidity-driven trades underperform valuation-motivated trades. Second, fund managers making purely valuation-motivated purchases generate significant characteristic-timing performance but are not able to do so when compelled to work off excess cash from investor inflows. On the other hand, fund managers are not able to produce characteristic-timing returns from their selling decisions, even when they are highly motivated by valuation beliefs. Furthermore, this third chapter explores whether different groups of mutual fund managers possess different skills. My results reveal that fund managers who possess superior selling ability are also significantly better at buying stocks than the remaining fund managers and as a result, these fund managers exhibit a significantly higher aggregate characteristic-timing returns. Strikingly, fund managers who appear to buy stocks well are not able to outperform other funds when selling stocks, and they exhibit no significant aggregate performance. Overall, these results highlight and reinforce the insight that fund managers have positive buying skill and negative selling skill.

In the fourth chapter, I study overconfidence among actively managed equity mutual fund managers. While there is ample evidence to show that retail investors are prone to overconfidence bias (e.g., Odean, 1999; Barber and Odean, 2000, 2001, 2002; Grinblatt and Keloharju, 2009), empirical evidence on overconfidence among professional investors is scarce. Using the sum of absolute deviations from the portfolio's benchmark index (i.e., Active Share) as a proxy for the confidence level of mutual fund managers, my results show that fund managers tend to boost their confidence after outstanding past performance: they are more likely to increase Active Share and also choose a much higher Active Share level. Consistent with the diversification of opinions hypothesis in the literature (e.g., Sah and Stiglitz, 1986 and 1988; Cooper and Kagel, 2005; Kocher and Sutter, 2005) overconfidence bias seems to be more pronounced among solo-managed funds than team-managed funds. More importantly, an inverted U-shaped relationship between confidence level and subsequent performance is uncovered. In particular, excessive overconfidence, as reflected by an extremely high level of Active Share, is associated with diminished future fund performance, as well as more extreme performance outcomes and greater performance dispersion. This chapter further documents irrational investor reactions to fund manager overconfidence. There is a marked bonus for good performance of overconfident managers, as rewarded by higher fund inflows than other funds with comparable performance, while there is no pronounced penalty for poor performance of overconfident managers.

Results from chapters 2 and 3 have meaningful implications for identifying fund manager skills and for understanding asset management in the real world. My results directly question the capability of the traditional evaluation approaches employed in the literature, which only consider aggregate mutual fund performance, to detect fund manager abilities. The lack of evidence of overall fund performance documented in the literature might mask the distinct buying and/or selling skills mutual fund manager really possess.

In terms of practical implications, my results seem to suggest that retail fund investors are perhaps well advised to select mutual fund managers who can manage to make sell decisions in a more disciplined way. Similarly, the investment industry can also benefit by considering differential trading skills in the fund manager selection process, rather than being heavily dependent on managers' past performance record in aggregate. Furthermore, a new compensation contract that rewards different investment tasks separately might keep fund manager well motivated to allocate their limited time and attention to what they are really good at.

Findings from the fourth chapter can also provide important implications, both to the academic literature and the investment industry. For example, my results highlight a potential issue of the simple linear regression approach employed in most previous studies on active management. The predictive power of active management measures such as Active Share and portfolio concentration in those studies might be over-estimated and as a result, lead to incorrect inference regarding fund manager skills. More importantly, my study support behavioural approaches to asset pricing (e.g., Barberis et al, 2001; Daniel et al, 2001; and Grinblatt and Han, 2005) with direct evidence that mutual fund managers are prone to overconfidence and associated behavioural biases. Since mutual fund managers are likely to be marginal price setters in stock markets, their irrational behaviours would not be easily arbitraged away and thus could cause asset price diverge from their information-efficient values.

Since the publication of Cremers and Petajisto (2009), fund managers are more aware of the importance of being “active”. Indeed, more active fund managers tout their Active Share, and several leading investment house strongly advocate the measure and voluntarily disclose Active Share level of their portfolios under management. On the other hand, fund investors seem to increasingly view Active Share as an essential indicator of fund mangers’ skill and a flawless predictor of fund future performance. My analysis highlights a strong positive relationship between outstanding past performance and Active Share level, suggesting that a significantly high level of Active Share is more likely to be driven by fund manager overconfidence and self-attribution bias, rather than manager skills. Not surprisingly, such high Active Share primarily driven by fund manager overconfidence underperform. Retail investors can benefit from these findings by starting to think more seriously about potential behavioural biases among fund managers when investing in mutual funds. My results seem to suggest that retail investors would better to stay away from overconfident fund managers to avoid unnecessary risks such as more extreme performance outcome and greater return dispersion.

Overall, I believe this thesis makes an original contribution to the literature on mutual fund performance evaluation and the behaviour of mutual fund managers. Its conclusions are also of direct practical relevance to both the fund management industry and investors in mutual funds. This thesis also provides the basis to develop further work along a number of different dimensions.

To further investigate the impact of overconfidence on subsequent fund performance and fund flows, future research can extend this chapter by introducing more trading behaviors that are commonly used to proxy for overconfidence including portfolio turnover, portfolio concentration, and idiosyncratic risk exposure. Odean (1998) theoretically shows that overconfident investors trade more frequently, hold larger positions in risky assets, hold more concentrated portfolios, and take greater risk than do “rational” investors. Barber and Odean (2001) provide evidence that investor overconfidence is positively related to portfolio turnover and risk. Similarly, Goetzmann and Kumar (2008) find that overconfidence is associated with under-diversification. However, there are other potential confounding factors may affect these trading behaviours, such as incentive for window dressing and tax management. To overcome this, we can follow Eshraghi and Taffler (2012), who employ narrative measures for overconfidence based on content analysis on the mutual fund annual reports and extend their work by combining these narrative-based proxies with the aforementioned trading behaviors.

The lack of performance persistence also provide fertile ground for future research. Berk and Green (2004) argue that in a competitive market superior performance form skilled fund managers is quickly bid away by fund investors. Given the adverse impact of fund manager overconfidence on subsequent fund performance I observed, overconfidence bias can provide one potential explanation for the weak performance persistence among successful fund managers documented in the literature (e.g., Carhart, 1997). In addition, another possible area for further investigation is the demographics factors which might influence fund manager overconfidence including education background, experience, location, and gender.

Although the fourth chapter of this thesis and other studies in the literature such as Eshraghi and Taffler (2012) have shown that overconfidence is associated with reduced future performance, the fundamental questions how, and through which mechanisms overconfidence affect investment performance still remain unclear. The findings of negative selling ability from the first and second chapter may provide a good research direction to solve these questions. If mutual fund managers become overconfident following outstanding performance, they tend to overestimate their investment abilities, and thus, are more likely to form their selling decisions in a much less disciplined way. Although this argument is intuitive and reasonable, the rigour of this subject requires a thorough investigation in this matter, in particular with data limitation on fund manager trades. Since institutional trading data are not publicly available, previous studies that examine trade performance have to rely on changes in quarterly holdings to proxy for trading activity. This noisy proxy, however, limit researchers' ability to identify superior investment skills, and perhaps more interestingly, capture the adverse impact of behavioral bias such as overconfidence. To overcome such data limitation and maximize test power, future research can employ high-frequency trading data provided by ANcerno Ltd (formally the Abel Noser Corporation)[7] to explore the effect of overconfidence bias on fund manager trade decisions and trade performance.

[7] See Puckett and Yan (2011) for a detailed description of ANcerno Database

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Appendix A

The screening procedure for U.S. domestic equity mutual funds I used in the thesis builds on Kacperczyk *et al* (2008). I start with a sample of all mutual funds in the CRSP Mutual Fund Database and eliminate 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). Then, I exclude 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 steps, I select 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, I include funds with Strategic Insight Objective Code (si_obj_cd) of "AGG", "GMC", "GRI", "GRO", "ING", and "SCG". If Strategic Insight Objective codes are missing, then funds with Wiesenberger Fund Type codes of "G", "G-I", "AGG", "GCI", "GRI", "GRO", "LTG", "MCG", and "SCG" are included. If none of the above objective codes are available, funds with a CS policy are included. If CS policy is not available, I exclude funds with average stock holdings less than 80% or more than 105% and fund that hold less than 10 stocks and that managed asset less than $5 million in previous month. In addition, I search for keywords in the fund full name and eliminate funds with keywords of "index", "idx", "S&P", "DFA", "program", "ETF", "exchange traded", "exchange-traded", "target", and target date funds. Following Alexander *et al* (2007), funds with less than four holdings reports that were each preceded by another report in the previous quarter are excluded from my final sample.